Near doubling of Brazil's intensive row crop area since 2000

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Brazil has become a global leader in the production of commodity row crops such as soybean, sugarcane, cotton, and corn. Here, we report an increase in Brazilian cropland extent from 26.0 Mha in 2000 to 46.1 Mha in 2014. The states of Maranhão, Tocantins, Piauí, Bahia (collectively MATOPIBA), Mato Grosso, Mato Grosso do Sul, and Pará all more than doubled in cropland extent. The states of Goiás, Minas Gerais, and São Paulo each experienced >50% increases. The vast majority of expansion, 79%, occurred on repurposed pasture lands, and 20% was from the conversion of natural vegetation. Area of converted Cerrado savannas was nearly 2.5 times that of Amazon forests, and accounted for more than half of new cropland in MATOPIBA. Spatiotemporal dynamics of cropland expansion reflect market conditions, land use policies, and other factors. Continued extensification of cropland across Brazil is possible and may be likely under current conditions, with attendant benefits for and challenges to development.

cropland expansion | land cover change | remote sensing | Brazil | area estimation

Growing demands in national and international markets for commodity crops drives increasing production through more intensive management practices, extensification through land conversion, or both. China's soybean imports, for example, increased from just less than $2 billion in 2000 to $35 billion in 2014 (1). This demand has led to dramatic production increases in countries such as Brazil (2–4), which has become a global leader in the cultivation of soybeans, as well as sugarcane, corn, and cotton (1). Intensification of existing agricultural land uses, such as the conversion of pasture to cropland, and extensification of agroindustrial cropping systems through the conversion of natural vegetation result in numerous externalities, including increased runoff of fertilizers and pesticides, overutilization of freshwater resources, greenhouse gas emissions, and biodiversity loss (5, 6). Knowing where croplands are expanding, their rate of expansion, and the land covers that they are replacing is essential to quantify current and model future environmental impacts. Improved information on cropland extensification also facilitates the study of supply chains and their respective economic and institutional contexts (7).

In Brazil, the topic of cropland expansion is particularly salient. Advances in technology, market liberalization policies, government subsidies, and favorable international prices accelerated the development of the cropland frontier. As production methods matured and soybean proved more profitable than cattle, soybean expansion was accelerated by increasing economies of scale (8–11). Research on land use and land cover change associated with cropland expansion in Brazil is extensive in the literature, but often limited in geographic or thematic scope. The main research focus has been on answering the question of whether crop expansion is a proximate driver of deforestation. Accordingly, there is a strong bias in the research literature toward the Amazon biome and the state of Mato Grosso (2, 12–16), where the dominant theme is deforestation driven by soybean expansion. The Cerrado biome, a biodiversity hotspot (17, 18), has recently become the focus of attention as a result of the rapid expansion of cropland in the region of MATOPIBA (an acronym for the names of the four states that compose this region, Maranhão, Tocantins, Piauí, and Bahia) (19–22). A number of studies have focused on São Paulo and Goiás, two states in the south-central region of Brazil that have been the site of dramatic expansion of sugarcane for biofuel production (23–25). However, few studies quantify changes in crop area at the national scale. Furthermore, most of the spatially explicit studies have employed coarse spatial resolution Moderate Resolution Imaging Spectroradiometer (MODIS) data (2, 12, 15, 16, 21, 22), limiting accurate cropland area estimation, particularly in the south of the country, where relatively smaller field sizes are predominant. A few studies have used census data provided by the Brazilian Institute of Geography and Statistics (IBGE) to characterize changes in cropland area at the national scale, but the last agricultural census was carried out in 2006. Another common data source used (13, 26) is the Sistema IBGE de Recuperação Automática (SIDRA) database, which provides crop areas estimated by experts, which, as such, are subject to inconsistencies through time. Products such as TerraClass (27, 28), TerraClass Cerrado (29) or Canasat (23, 30) at medium spatial resolution are also limited in temporal and geographic scale. A new project focusing on mapping at biome scale for the entire record of Landsat,

Significance

As Brazil's cropland expands as a result of increasing demand for commodity crops, new croplands replace existing land covers and land uses. Our study employs the most spatially detailed historical record of satellite imagery available to show that the area of intensive row cropping in Brazil nearly doubled from 2000 to 2014 mainly because of the repurposing of pastures (80% of new cropland) rather than conversion of natural vegetation (20%). Trends of cropland expansion through time may be linked to land use policies, market conditions, and other factors. Although evidence suggests that land use policies slowed cropland expansion within Amazon rainforests, no such decrease was found for Cerrado savannas, which experienced 2.5 times the natural vegetation conversion of the Amazon biome.

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called MapBiomas (31), holds promise. However, no published area-change studies have followed good practice guidance (32–38) in which a sample of reference data are used to provide an unbiased area estimate of cropland cover expansion accompanied by an SE that quantifies the uncertainty of the area estimate. As a result, a comprehensive and definitive national-scale record of yearly land cover changes related to cropland expansion in Brazil is lacking.

Remote sensing data provide a unique resource for measuring such changes consistently over space and through time, facilitating a common understanding among policymakers, civil society, scientists, and private industry. For the present study, cropland is defined as the land area under intensively managed, agroindustrial row crops consisting of commodity crops such as soybean, sugarcane, cotton, corn, rice, and wheat. We employ 30-m spatial resolution Landsat data to estimate cropland extent in the year 2000 and its subsequent expansion through 2014. A probability sample of reference data allows us to report unbiased estimates of national-, biome-, and state-scale area of crop expansion with associated uncertainties. Through our sample assessment, we disaggregate crop expansion by year and by previous land cover type to produce estimates of temporal trends of area of crop expansion by repurposing of pastures (defined as lands dominated by herbaceous cover used for grazing livestock) and by conversion of natural vegetation cover. These results represent definitive, precise, and unbiased estimates of national-scale cropland expansion in Brazil.

Results

Cropland extent in the year 2000 in Brazil was 26.0 ± 1.1 Mha (the uncertainty is expressed as ±1 SE of the estimate). In the subsequent 14-y period, cropland expanded by 20.5 ± 1.6 Mha, representing a 79% increase relative to the year 2000 cropland area. We define the states that more than doubled their respective cropland area since 2000 as constituting the cropland frontier: Mato Grosso, Mato Grosso do Sul, Pará, Bahia, Maranhão, Piauí, and Tocantins (Fig. 1*A*). Cropland loss was limited to 0.7 ± 0.1 Mha for the entire country during the study period. *SI Appendix*, Table S1 provides accuracy assessment results, and *SI Appendix*, Fig. S1 shows classification results. *Methods* provides detailed information on reference data interpretation.

The state with the largest area of new cropland was Mato Grosso, with 4.4 ± 0.5 Mha of cropland in 2000 and 5.3 ± 0.8 Mha of cropland gain through 2014. Cropland expansion in Mato Grosso represents 26% of the total cropland expansion area in the country. The biome with the greatest area of new cropland was the Cerrado, with 10.5 ± 1.0 Mha of additional crop area by the end of the study period (81% increase vs. 2000). Cerrado cropland expansion represents 52% of the total expansion in the country (Fig. 1*B*).

Brazilian cropland expanded rapidly and peaked during the 2004/2005 growing season, followed immediately by a sudden and pronounced decrease in annual expansion area (Fig. 2). After a low in 2006/2007, the rate of cropland expansion by 2013/2014 approached that of the 2004/2005 peak. The rapid increase through 2004/2005 and subsequent rapid decrease of cropland expansion area was most pronounced in the states of Mato Grosso and MATOPIBA and the Amazon and Cerrado biomes (*SI Appendix*, Figs. S4 and S5). Nearly every state and biome for which we have data available experienced a decrease in cropland expansion in 2004 (*SI Appendix*, Figs. S4 and S5). Since the decrease in the 2004/2005 growing season, the rate of crop expansion has steadily increased in most states, with Mato Grosso do Sul, Minas Gerais, Goiás, and Piauí having the most rapid increase in cropland area after 2005 (*SI Appendix*, Fig. S4). Every state and biome exhibited a peak in cropland expansion between 2011 and 2014 except for Maranhão and the Caatinga biome (*SI Appendix*, Figs. S4 and S5).

Pasture conversion was the source of nearly 79% of new cropland area in Brazil, and 20% was the result of conversion of natural vegetation, including Amazon humid tropical forests and Cerrado dry tropical woodlands and savannas. Only 1% of the total expansion area was created through the conversion of tree plantations. The overall proportion of cropland expansion within natural vegetation remained relatively constant at ∼20% throughout the study period, albeit with substantial regional variation. The MATOPIBA region had the largest proportion of natural vegetation conversion to cropland (57 ± 15%), consisting largely of Cerrado conversion (Fig. 3 and *SI Appendix*, Fig. S3). In the Amazon biome, 30 ± 2% of new cropland resulted from natural vegetation conversion, primarily of dense humid tropical forests (Fig. 3). The southern states of Mato Grosso do Sul, Paraná, Rio Grande do Sul, and São Paulo expanded their cropland area mostly through the conversion of pastures (99%, 99%, 88%, and 93%, respectively). Note that the areal increase of one crop, e.g., sugarcane (39), at the expense of other row crops would not meet our definition of cropland gain. Summary statistics and time-series graphs of cropland gain for all states and biomes having at least 10 sample pixels in the "cropland expansion" class are shown in Dataset S1 and *SI Appendix*, Figs. S4 and S5 and Table S2. *SI Appendix*, Fig. S2 provides a list of states and biomes for which we estimate cropland expansion areas.

Discussion

Comparison with Existing Datasets. Our results differ from existing estimates on cropland area and cropland area expansion in several ways. *SI Appendix*, Table S3 provides a comparison of the technical characteristics of our results and other available studies

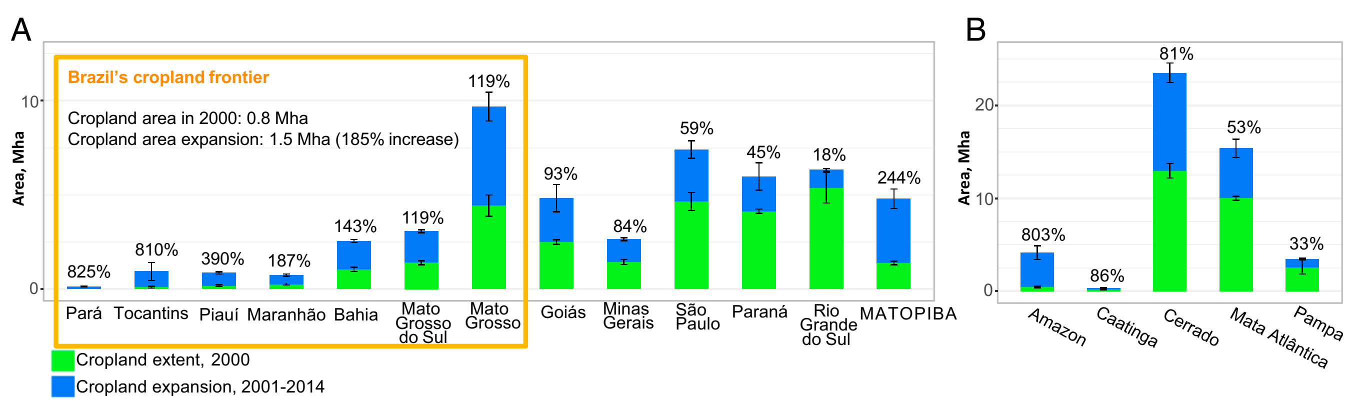

Fig. 1. Estimated area of cropland extent in 2000 and area of cropland expansion from 2001 to 2014: Brazilian states (*A*) and biomes (*B*). *SI Appendix*, Fig. S2 shows the location of states and biomes and for area included in MATOPIBA region. Numbers on top of bars indicate percent increase in cropland area since 2000. Error bars represent ±1 SE. Estimates are presented only for states and biomes that have >10 sample pixels in the "cropland expansion" strata.

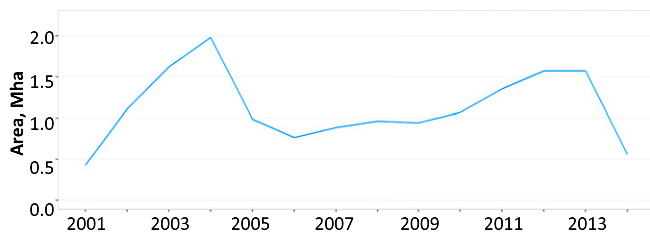

Fig. 2. Estimated annual cropland expansion area in Brazil from 2001 to 2014. Yearly trends are based on "cropland 2000" and "cropland expansion" strata. Year of expansion corresponds to year of planting (e.g., 2001 corresponds to the 2001/2002 growing season). Sample pixels from the "no cropland" strata add 4.7 ± 1.6 Mha to the total cropland expansion area shown here; this area is not displayed in the figure because it is not representative of yearly trends. Dataset S1 shows tabular data for all strata.

and data sources. Our study advances current knowledge on Brazilian cropland extensification as a result of its spatial extent (we present results at the national level but also disaggregate by states and biomes), its temporal extent (comparable to MapBiomas), and, most importantly, because it adheres to good practice recommendations (32–38) on area estimation and accuracy assessment. Unlike previous research, our study uses a probability sample of reference data for area estimation and provides uncertainty estimates (i.e., SEs) for the area estimates. Finally, our results provide information on pasture conversion to cropland, which is largely lacking in the literature.

Official estimates of cropland area available through the SIDRA database are widely used in the literature to study land use changes in Brazil (3, 13, 40, 41). These data are not directly comparable with our results because IBGE's area numbers double-count the area of a field if it is double-cropped. Dias et al. (3) use these numbers in their study and therefore significantly overestimate cropland land use area in Brazil (*SI Appendix*, Fig. S9). Barona et al. (13) also cite double-cropping as a possible source of overestimation of cropland area in their analysis.

To compare our results vs. data from the SIDRA database, we tried to approximate an estimate of cropland cover area based on their "planted area" metric by removing the area of secondary crops as well as areas of crops that do not fit our cropland definition (i.e., intensive row crop agriculture). To do this, we started out by adding together the areas of Brazil's most important crops: soy, corn, sugarcane, beans, rice, wheat, manioc, and cotton. These eight crops make up 95% of the total crop planted area in Brazil. We then removed the area of second-crop corn as well as second and third crops of beans. Although cotton is also used a secondary crop in crop rotations, data on cotton as a second crop are not available through the SIDRA database, so we included all of the cotton planted area in our area estimate. We also subtracted wheat area because wheat is a winter crop that is almost exclusively double-cropped. Finally, we removed the area of planted manioc because manioc production in Brazil is mostly small-scale and nonintensive, which excludes it from our cropland class definition (it is not produced as an intensive row crop). The result, which we refer to as the IBGE Land Cover (LC) estimate, corresponds to 35.7 Mha in 2000 and 52.5 Mha in 2014 (*SI Appendix*, Fig. S9).

These estimates are higher than the ones we present in our study. There are many possible reasons why IBGE LC estimates may differ from ours. Area estimates provided by IBGE are the result of expert surveys and, as such, they are, to some degree, inherently inconsistent across space and time. Additionally, IBGE does not provide any indication of the accuracy or the uncertainty of their statistics. As a result, IBGE statistics may not always be the most appropriate data source for land cover change studies related to changes in cropland area in Brazil. Indeed, several authors have pointed to the limitations of IBGE statistics and called for the need for higher-quality cropland maps for Brazil (3, 13, 40).

Another important dataset that holds promise for cropland extent and expansion monitoring is MapBiomas (31). MapBiomas provides Landsat-based maps of land cover disaggregated into 5 broad categories (and as many as 15 detailed categories) for every year from 1985 to 2017. One of these categories is "farming," which they disaggregate into "pasture," "agriculture," and "agriculture or pasture" for areas of confusion between the two. We compared their results from the agriculture category with our results and found that their results approach ours. At the national level, we report lower area estimates than they do; in Mato Grosso, their results are similar to ours; and in the Cerrado biome, we report higher area estimates (*SI Appendix*, Fig. S9). Their results for cropland expansion diverge substantially from our results (*SI Appendix*, Fig. S8). The main limitation of the MapBiomas product is that they do not follow current good practice guidance (32–38), which recommends estimating area from the reference sample observations and assessing accuracy of the mapped land cover change. The latest version of the MapBiomas project (Collection 3.0) does not yet have an accuracy assessment of any type.

Additionally, the TerraClass Amazon and TerraClass Cerrado products provide data on land cover at Landsat resolution for the Amazon and Cerrado biomes, respectively. The limitations of these products compared with the results obtained through the present study are that (*i*) maps are available only for certain years, (*ii*) they do not provide accuracy assessment of change classes, and (*iii*) they do not employ good practice recommendations (32–38) for area estimation and associated uncertainties. IBGE also provides data on cropland area through their Systematic Monitoring of Land Use project (42), which maps land use and land cover change in Brazil for the years 2000, 2010, 2012, and 2014. This product has the same limitations as the ones listed for the TerraClass products, among others (an additional limitation of this product is its minimum mapping unit of 62.5 ha; *SI Appendix*, Table S3).

Comparisons of cropland expansion, total cropland area, and conversion of natural vegetation to cropland between the present

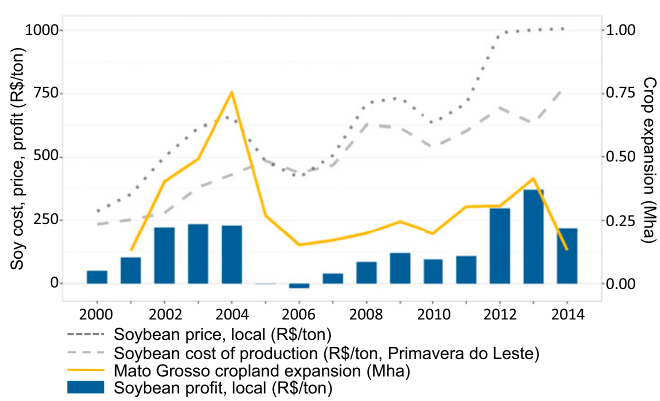

Fig. 3. Soybean terms of trade in Mato Grosso. Mato Grosso cropland expansion from this study is compared with soybean price and cost of production. Soybean price is the nominal producer price, obtained from the Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) (49). Soybean cost is from Companhia Nacional de Abastecimento (CONAB) (50). Mato Grosso cropland expansion is derived from the sample-based area estimate for the "cropland 2000" and the "cropland expansion" strata (Dataset S1 shows tabular data). Year of expansion corresponds to year of planting (e.g., 2001 corresponds to the 2001/2002 growing season). FAOSTAT and CONAB data display is adapted from Arvor et al. (40).

study and other studies and datasets (2, 3, 12, 21, 22, 31, 42–45) are provided in *SI Appendix*, Figs. S8–S10.

Trends in Cropland Expansion. National-scale dynamics of cropland expansion in Brazil from 2000 through 2014 reflect an early peak in the 2004/2005 growing season, followed by a sharp decrease and subsequent gradual recovery to near 2004/2005 levels by 2013/2014 (Fig. 2). Here, we discuss a number of policy, management, and economic factors that may have played a role in shaping trends of cropland expansion in the region. Establishing cause-and-effect relationships between these factors and the land cover changes discussed requires further research, which would be enabled by accurate cropland expansion area estimates such as presented in this study.

The 2005/2006 decrease in crop expansion in Brazil coincides with a period of unfavorable market conditions (2, 46–49). A decrease in soybean prices, the appreciation of the Brazilian real relative to the US dollar, and an increase in costs of production linked to high oil prices caused soy profits to decrease dramatically from 2004 to 2005. As a result, farmers in Mato Grosso were faced with negative profit margins for soybean production in 2005 and 2006, which might have disincentivized expansion (Fig. 3). Added to these economic factors was a severe drought during the 2004/2005 growing season (49, 50). Our estimates of annual cropland expansion in Mato Grosso closely mirror data on annual soybean profit (Fig. 3). The largest residual is related to the period of greatest expansion in 2004, with dramatic decreases in profits and expansion the following year. Peak cropland expansion post-2004 is observed in the 2013/2014 growing season, the year of greatest soybean profit during the study period for Mato Grosso. Morton et al. (12) and Macedo et al. (2) have cited soy profitability as a potential influencing factor on trends of forest conversion to cropland (*SI Appendix*, Fig. S10 shows a comparison of their results vs. results from the present study). Our results support this hypothesis.

Humid tropical forests in the Brazilian Amazon have experienced the highest rates of deforestation globally in recent decades (51, 52). Drivers of deforestation include pasture land use for beef production and cropland land use for soybean production. Because of the extraordinary ecological significance of the Amazon biome, international attention and national policies have focused on slowing deforestation, with unprecedented success (22, 26, 40, 46). A number of policy initiatives and supply-chain interventions have contributed to the reduction of deforestation in the Brazilian Amazon. These include an increased capacity for enforcement of the forest code by the government through the implementation of the Detection of Deforestation in Real Time program in 2004 (53), the implementation of an Action Plan allowing coordination among agencies and ministries at the federal level to combat deforestation in 2004 (40), the rapid expansion of the protected area network starting in 2002 (54), and a successfully implemented multistakeholder moratorium on sourcing soybeans from newly deforested lands starting in 2006 (22, 46, 55).

We find that cropland expansion into forests in the Amazon began to slow in 2004/2005, reflecting a possible response of land owners to policies (and the anticipation of pending policies), market conditions, or both (Fig. 4). After 2006, conversion of forests to cropland in the Amazon remained consistently low. This result supports existing findings on the decrease of cropland expansion into deforested areas during this time period (2, 12) and has been linked to the Soy Moratorium (22, 46). At the same time, conversion of pastures to cropland began to increase. The primary target area for the Soy Moratorium, the state of Mato Grosso, experienced decreased clearing of natural vegetation for cropland after 2004 (Fig. 4). Cropland expansion within natural vegetation in MATOPIBA, a region that is outside the reach of the Soy Moratorium, did not experience a similar sustained decrease, and increased slightly over the study period

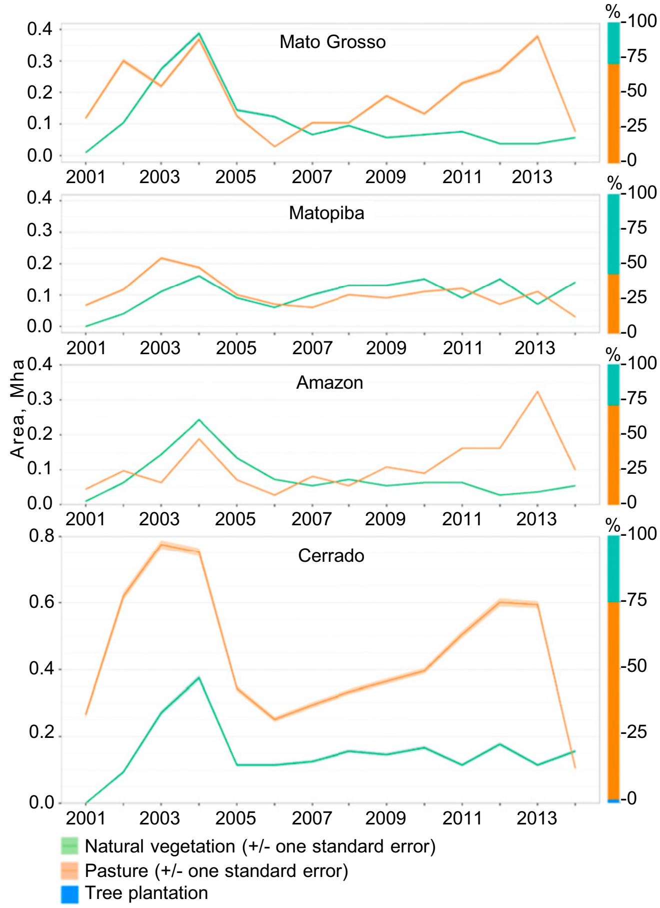

Fig. 4. Trends in cropland expansion disaggregated by conversion from pasture and natural vegetation for Mato Grosso, MATOPIBA, the Amazon biome, and the Cerrado biome. Bars on the right represent cumulative share of pasture and natural vegetation as source of new cropland for 2001–2014. Trends shown reflect sample-based area estimates of cropland expansion for "cropland 2000" and "cropland expansion" strata. Year of expansion corresponds to year of planting (e.g., 2001 corresponds to the 2001/2002 growing season). Sample pixels from the "no cropland" strata are not displayed. Dataset S1 shows tabular data for all strata.

(Fig. 4). The trends in converting pastureland to cropland also differ, with Mato Grosso experiencing a dramatic increase over time following a minimum expansion area within pastureland in 2006/2007.

Two possible impacts of the regulatory measures implemented in the Amazon (e.g., Soy Moratorium and other public policy initiatives) are shown in Fig. 4. First, the ratio of new cropland converted from pastureland vs. converted from natural vegetation for Mato Grosso increases from 1.1:1 from 2001 to 2004 to 4.3:1 from 2011 to 2014, reflecting the strategy of adding soybean area within already deforested lands. Second, the same ratios for MATOPIBA change from 1.3:1 to 0.7:1, possibly reflecting leakage of cropland expansion pressure to a region that is largely unconstrained by regulatory limits. The potential for leakage of cropland expansion from the Amazon to the Cerrado's MATOPIBA states has been discussed in the literature (21, 22), but there has been limited evidence until now because of the paucity of spatiotemporally consistent cropland datasets for both regions. Determining whether there is a cause-and-effect relationship between policies aimed at slowing humid tropical deforestation and increased clearing in MATOPIBA requires additional study. It is indeed possible that the conversion of natural vegetation areas in MATOPIBA would have occurred regardless of policies in the Amazon as a result of favorable market conditions, infrastructure development, or land suitability.

By combining the Global Forest Change (GFC) maps (52) with the cropland expansion map, we are able to observe regional patterns of forest conversion to cropland during the study period (Fig. 5). The resulting map illustrates the decrease in the conversion of tree cover (defined as ≥5 m trees and ≥30% tree canopy cover) to intensive cropland within the Amazon after 2005 and a corresponding increase in the conversion of tree cover to cropland within the Cerrado starting in 2006. The spatial pattern and temporal dynamics are confirmed through our probability sample assessment in estimating natural vegetation cover conversion (Fig. 6). The conversion of low/no tree cover Cerrado vegetation in Mato Grosso and MATOPIBA is substantial and not captured in the global forest loss data (*SI Appendix*, Fig. S2). This result highlights the need for spatially explicit maps of natural shrublands and nonwoody vegetation cover types in addition to tree cover in assessing the impacts of cropland expansion on natural ecosystems such as the Cerrado.

Another factor probably impacting cropland dynamics has been the advent and spread of soybean rust. At the beginning of the study period, Brazilian farmers were “unaware of the presence” (50) of the fungus, which left them unprepared to manage its effects. Year-on-year increases in lost production reached a peak in 2004 with 4.6 million tons of grain lost (50). Formal interventions to limit soy rust included new planting strategies such as the implementation of an annual 90-d soybean-free period starting in 2007 and 2008. Fungicide treatments in combination with double-cropping practices and the introduction of new soybean varieties have further reduced soybean rust losses (50). The role of soybean rust in mediating investment in new croplands during the study period must be considered along with other factors.

Cropland expansion is not limited to the cropland frontier states where cropland area more than doubled. Even historically established agricultural states experienced substantial increases in crop area. In absolute terms, São Paulo, Goiás, Paraná, and Mato Grosso do Sul each followed Mato Grosso and MATOPIBA in area of new cropland. The Mata Atlântica biome, with 5.4 ± 1 Mha of new cropland, was second to the Cerrado in total area of cropland area increase, reflecting a dramatic repurposing of pasture land uses. Just more than 1% of Mata Atlântica cropland expansion consisted of conversion of natural vegetation. However, cropland expansion in Brazil’s southern states has been linked to deforestation in the Amazon through the displacement of cattle-ranching activities (56, 57), which would indirectly increase the environmental costs of this type of land cover change. Results for the Mata Atlântica and Pampas reveal that, despite substantial intensification in recent years (3, 4), cropland extensification remained a potential pathway for increased crop production across Brazil during 2000–2014. States experiencing nascent agricultural investment, such as Roraima and Amapá (58), represent the next potential frontier of Brazilian cropland expansion (we do not have cropland area estimates for these regions because they did not have substantial enough cropland areas during our study period).

As Brazil’s agricultural sector grows in response to internal and global market demands, accurate and transparent geospatial

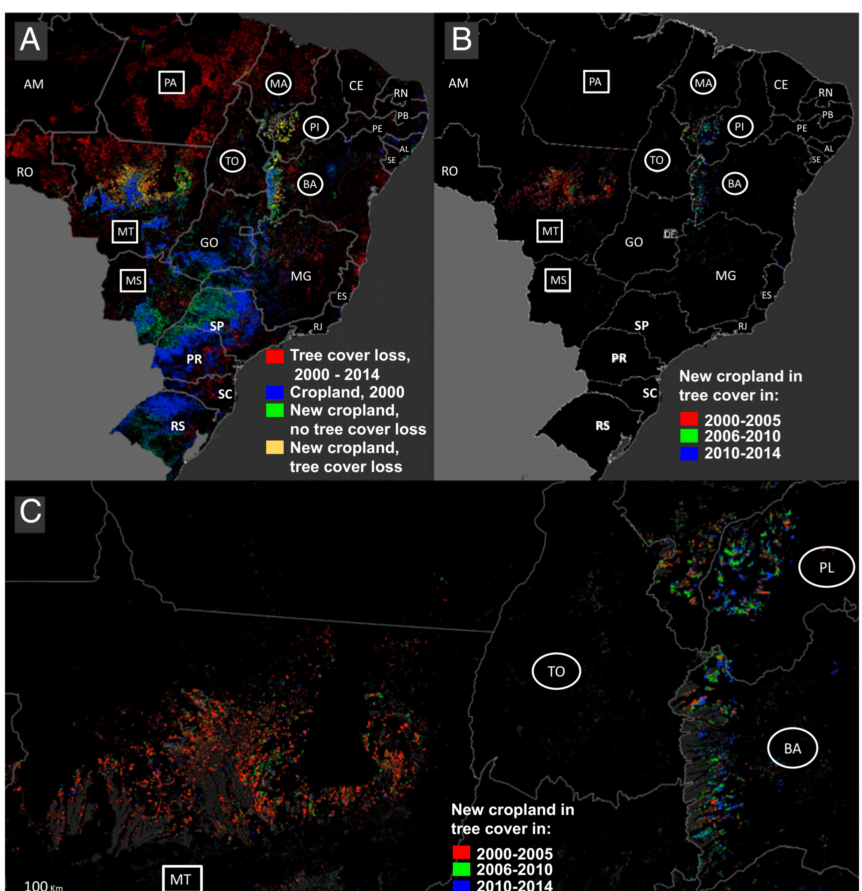

Fig. 5. Regional patterns of forest conversion to cropland: (*A*) cropland extent in 2000 (green), cropland gain outside (blue) and inside of tree cover (yellow) through 2014, and tree cover loss unrelated to cropland expansion (red). (*B*) Cropland gain inside tree cover disaggregated by epoch. MATOPIBA states are shown in ellipses, and other states with cropland increases of greater than 100% are shown in boxes. (*C*) Subset of *B* centered on Mato Grosso and MATOPIBA states.

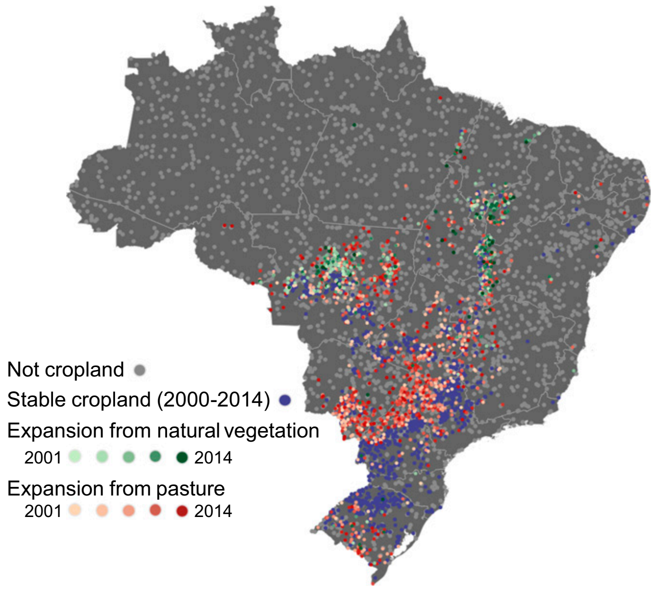

Fig. 6. Geographic distribution of the 5,000 sampled pixels classified by reference cropland type (stable/expansion/not cropland), previous land cover type, and year of change.

data depicting this dynamic are needed. In this study, we have presented unbiased and precise estimates of Brazilian cropland expansion area nationally and at the scale of major production states and biomes. These methodologically consistent estimates, along with our corresponding spatiotemporal data (i.e., maps of 2000 cropland and 2000–20014 cropland expansion), contribute to enhanced understanding of the economic, policy, social, and environmental drivers and outcomes of the rapid and large-scale expansion of agroindustrial land uses. Our results for the dynamic time period of 2000–2014 reflect the dramatic growth of commodity crop land use in Brazil driven primarily by repurposing pasture land and converting natural vegetation. Extending these analyses to the beginning of the Landsat record (circa 1984) and forward in time will provide estimates and data that can be used to gain further insight regarding the response of cropland expansion to market conditions, disease, and other factors, as well as the impact of land-use policies in redistributing expansion pressures.

Methods

Landsat time-series data were used to map Brazil into the following categories: 2000 cropland, 2000–2014 cropland gain, and no cropland. The mapped classes were used as an input to a stratified random sample of reference data consisting of MODIS, Landsat, and Google Earth imagery to estimate the area of year 2000 cropland and 2000–2014 cropland expansion.

Landsat Data. Two sets of Landsat data were used to create the maps: all available Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data for 1999–2001 and all available Landsat 7 ETM+ and Landsat 8 Operational Land Imager (OLI) for 2011–2014. All the images were downloaded from the United States Geological Survey Earth Resources Observation and Science Center in the L1T terrain-corrected format. Inputs for the land cover classification were derived from spectral bands that are not as sensitive to atmospheric contamination and scattering (59): red (ETM+ 0.630–0.690 μm and OLI 0.630–0.680 μm), near-IR (ETM+ 0.775–0.900 μm and OLI 0.845–0.885 μm), and two shortwave IR (SWIR), SWIR1 (ETM+ 1.550–1.750 μm and OLI 1.560–1.660 μm) and SWIR2 (ETM+ 2.090–2.350 μm and OLI 2.100–2.300 μm). Blue (ETM+ 0.45–0.52 μm and OLI 0.45–0.51 μm) and green (ETM+ 0.525–0.605 μm and OLI 0.525–0.600 μm) bands were used only for quality assessment (QA) of viable observations. The thermal band (ETM+ 10.40–12.50 μm and Landsat 8 Thermal Infrared Sensor 10.60–11.19 μm) was used for QA and for creating rank-based multitemporal metrics.

Topography Data. Ninety-meter-resolution Shuttle Radar Topography Mission (60) digital elevation model (DEM) data were also used as an input for classification. The elevation layer was reprojected via cubic spline to 0.00025° to match the Landsat resolution. Slope and aspect calculated from this elevation layer were used as additional inputs.

Auxiliary Data for Image Interpretation. Time series of 16-d MODIS Normalized Difference Vegetation Index (NDVI) (61) composites and Google Earth high-resolution imagery were used only for interpretation of training set and reference samples. The high temporal frequency of MODIS reflecting crop phenology helped to distinguish between crop and pasture pixels.

Landsat Data Processing. Landsat data processing was undertaken independently for both data sets (1999–2001 and 2011–2014) following methods developed for global data processing (62). First, we converted raw digital numbers to top-of-atmosphere (TOA) reflectance and brightness temperature by using established methods (63). Second, we used a set of existing quality-assessment models (existing sets of bagged decision trees) to get a per-pixel QA flag for cloud, shadow, haze, and water detection. Third, we applied a radiometric normalization by using a cloud-free surface reflectance MODIS composite as a normalization target. The mean bias per band between the MODIS and Landsat TOA reflectance was calculated and successively applied to adjust Landsat reflectance. Finally, we corrected for cross-track reflectance anisotropy by regressing the bias between Landsat TOA and MODIS surface reflectance against the Landsat scan angle. The slope and intercept of this regression were used to correct reflectance values per band, per image. These steps are part of an established Landsat processing system that has been successfully applied in a number of studies (52, 62, 64).

Metric Creation. Multitemporal metrics allow us to capture phenological changes in vegetation within a consistent and standardized spatiotemporal feature space (52, 65). They facilitate regional-scale mapping using Landsat data despite variability in observation counts. Landsat processing steps are performed at the image level, whereas metric creation is a per-pixel process. Two sets of multitemporal metrics were created by using the data from each time period (1999–2001 and 2011–2014). To create one of these sets, we started by pooling together all cloud-free observations and ranking them based on (*i*) band reflectance value, (*ii*) NDVI, (*iii*) Normalized Difference Water Index (NDWI), and (*iv*) brightness temperature. We created two types of metrics: rank-based metrics and average-based metrics. Rank-based metrics represent the minimum, maximum, and 10th, 25th, 50th, 75th, and 90th percentiles of surface reflectance for the red, near-IR, and both shortwave bands and for the NDVI and NDWI for each rank method. Average-based metrics represent the averages for the following percentile intervals for each rank method: minimum to 10th, 10th to 25th, 25th to 50th, 50th to 75th, 75th to 90th, 90th to maximum, minimum to maximum, 10th to 90th, and 25th to 75th. Additional metrics were derived by applying a moving average filter to all existing metrics by using a 3×3 kernel. When we had obtained a multitemporal metric set for each time period, a third metric set was created by taking the difference of the corresponding average-based metrics from both time periods. These metric sets, along with the DEM and slope layers, were used as inputs for the classifications. In total, approximately 650 metrics were used for the cropland 2000 classification, and approximately 1,350 for the cropland expansion classification.

Classification. For this study, we created two separate map products: a map of cropland extent in Brazil for the year 2000 and a map of cropland expansion in Brazil from 2000 to 2014. We define the cropland land cover as areas of intensive row crop agriculture. To create the cropland expansion map, we targeted expansion between 2000 and 2014 as a class, as opposed to deriving cropland change from postclassification of annual maps of cropland from 2001 to 2014. Postclassification comparisons can lead to significant inaccuracies because of the confusion between real land-cover change and apparent change caused by misclassification errors. Both maps were created by using supervised bagged classification tree models (66). Training data were manually labeled by using Landsat cloud-free mosaics. Google Earth data and MODIS NDVI time-series data were used as additional inputs to aid interpretation. Classification trees work by recursively splitting the training dataset into increasingly homogenous groups until a certain purity criterion is met. Seven bagged classification trees were used per model, each derived from a random sample of 20% of the total training data set to avoid overfitting. The cropland extent map for the year 2000 was created by using the 1999–2001 metric set as independent variables for the classification. To create the cropland expansion map, we used all three metric sets described above. Both classifications were done iteratively by checking the classification results and adding more training in areas where the results were poor. Obtaining models that produced sufficiently accurate results needed several iterations because of the large spectral differences between different crop types, agricultural practices, and crop calendars, as well as because of confusion with other land cover types such as pasture and shrubland. *SI Appendix* includes further information on which metrics were most important for classification.

Accuracy Assessment and Sample-Based Area Estimation. All maps contain errors, which is why land cover area estimates should be based on a probability sample of reference data (32–38). Aside from producing unbiased area estimates and associated uncertainties, sampling allows us to add value to land cover change studies by including attributes regarding date and type of change (51, 67, 68). Information in this study related to previous land cover type and year of change was attributed through sample interpretation and not by using auxiliary land cover maps. Other studies (12, 21, 22, 43) have used maps of deforestation or land cover to determine previous land cover type and derive areas of conversion from forest to cropland, but the results from such studies are prone to bias of area estimates caused by map classification error (32–38).

For our study, a stratified random sample of 5,000 30 × 30-m pixels was selected. Crop area in 2000, total crop expansion from 2000 to 2014, and crop expansion per year from 2000 to 2014 were estimated from this sample. The three strata used in the sampling design were cropland 2000, cropland expansion, and no cropland (i.e., all pixels not included in the previous two categories), whereby the stratum to which a pixel was assigned was determined from the 2000 cropland and the 2000–2014 cropland expansion maps. The cropland expansion stratum was allocated 2,000 sample pixels to reduce the SEs of the area estimates of expansion by year and by previous land cover type. The remaining 3,000 sample pixels were allocated evenly between the cropland 2000 and no-cropland strata. Map accuracy and sample-based area estimates were calculated from the confusion matrix (32, 33).

The reference class label for each sampled pixel was determined based on expert interpretation of annual cloud-free Landsat image composites for 2000–2014, MODIS NDVI time series, and Google Earth high-resolution imagery time series, as available. A Web interface was built to aggregate the different sources of data for each sample pixel (*SI Appendix*, Figs. S6 and S7). Each sample pixel was labeled as one of four classes: stable cropland (i.e., the pixel belonged to the cropland class every year from 2000 to 2014), cropland expansion (i.e., the pixel was not cropland in the year 2000 but it became cropland in any of the following years), cropland loss (i.e., the pixel was cropland in the year 2000 but it changed to a different land cover in any of the following years), or not cropland. We consider "cropland 2000" and "stable cropland" to be equivalent classes because the amount of cropland loss over the 14-y time period was found to be negligible. If the sample pixel exhibited cropland expansion, we also recorded the year of expansion and the previous land cover type (pasture, natural vegetation, or tree plantation).

Spectral, temporal, and spatial/contextual information domains of the reference remote sensing data facilitated interpretation. For example, pastures have a higher albedo than natural savanna vegetation as a result of the effects of grazing pressure at the per-pixel scale. However, distinguishing pasture from herbaceous Cerrado natural vegetation (such as Campo Limpo grasslands) can be challenging when using only per-pixel spectral data. To facilitate discrimination, we examined landscape context, such as the presence of paddock or pasture boundaries, roads, and watering holes (high spatial resolution data provide more definitive evidence for more detailed features such as watering holes). Landscape context was also the primary information source used to discriminate forestry land use from natural forests. For pixels that exhibited a land cover transition from forest to pasture to cropland, we assigned forest as the previous land cover type if three or fewer years passed between the pasture to cropland transition. Otherwise, those pixels were labeled as conversion from pasture. All area estimates reported throughout this paper are sample-based and have known uncertainties (i.e., SEs) following good practice recommendations for estimating area (32–38). *SI Appendix* includes detailed results describing accuracy of the map used to create the sampling strata, along with an assessment of our sample interpretations against a dataset of field-verified samples.

GFC Map. To better understand the spatiotemporal patterns of cropland expansion into previously forested areas, we combined our cropland expansion map with the GFC map from Hansen et al. (52) The GFC map shows forest loss (defined as a stand-replacement disturbance) at 30-m resolution, and is disaggregated by year of loss event from 2001 to 2014. As previously mentioned, area estimates related to year of change and previous land cover type were derived from sample interpretation alone and not from the combination of our cropland maps with the GFC map. The combination of our cropland maps with the GFC map does provide a spatial representation of where cropland expansion was most likely to have occurred. This spatial display augments the sample-based area estimates that quantify the cropland expansion area but do not indicate where this expansion is occurring.

Data Availability. All data from the study, including maps, sample reference data, and tabular results, may be found at https://glad.geog.umd.edu/near-doubling-brazil-cropland-area-2000.

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