Assessing multidimensional sustainability: Lessons from Brazil's social protection programs

Cecilie Dyngeland[a,1], **Johan A. Oldekop**[b], **and Karl L. Evans**[a]

[a]Department of Animal and Plant Sciences, The University of Sheffield, Sheffield S10 2TN, United Kingdom; and [b]Global Development Institute, The University of Manchester, Manchester M13 9PL, United Kingdom

Edited by Arild Underdal, University of Oslo, Oslo, Norway, and approved July 14, 2020 (received for review November 28, 2019)

Examining linkages among multiple sustainable development outcomes is key for understanding sustainability transitions. Yet rigorous evidence on social and environmental outcomes of sustainable development policies remains scarce. We conduct a national-level analysis of Brazil's flagship social protection program, Zero Hunger (ZH), which aims to reduce food insecurity and poverty. Using data from rural municipalities across Brazil and quasi-experimental causal inference techniques, we assess relationships between social protection investment and outcomes related to sustainable development goals (SDGs): "no poverty" (SDG 1), "zero hunger" (SDG 2), and "health and well being" (SDG 3). We also assess potential perverse outcomes arising from agricultural development impacting "climate action" (SDG 13) and "life on land" (SDG 15) via clearance of natural vegetation. Despite increasing daily per capita protein and kilocalorie production, summed ZH investment did not alleviate child malnutrition or infant mortality and negligibly influenced multidimensional poverty. Higher investment increased natural vegetation cover in some biomes but increased losses in the Cerrado and especially the Pampa. Effects varied substantially across subprograms. Conditional cash transfer (Bolsa Familia [BF]) was mainly associated with nonbeneficial impacts but increased protein production and improved educational participation in some states. The National Program to Strengthen Family Farming (PRONAF) was typically associated with increased food production (protein and calories), multidimensional poverty alleviation, and changes in natural vegetation. Our results inform policy development by highlighting successful elements of Brazil's ZH program, variable outcomes across divergent food security dimensions, and synergies and trade-offs between sustainable development goals, including environmental protection.

rural development | environmental impact | food security | land use change | impact estimation

Sustainability is an elusive societal goal requiring transitions across multiple dimensions—including food security, poverty alleviation, health, and environmental protection (1). These major global challenges are interrelated (2) and are reflected in national and international development agendas, including the SDGs (3).

Food insecurity (SDG 2) remains an intractable global problem (4). Addressing it requires meeting multiple objectives simultaneously: enough healthy and nutritionally diverse food needs to be produced and available at all times to a population with physical and economic access to it (5). Food security is directly linked to poverty alleviation (SDG 1) and SDG 3 (6). However, agricultural production is also a key driver of natural vegetation and biodiversity loss (conflicting with SDG 15) and greenhouse gas emissions (conflicting with SDG 13) (7, 8).

Understanding synergies and trade-offs among multiple sustainability objectives and how they are influenced by policy interventions has been a key focus of scholarly and policy discussions around the globe (9). Despite recent methodological advances in causal impact estimation empirical research which quantifies synergies and trade-offs among diverse social and environmental outcomes from poverty alleviation programs is still extremely rare (10). There is a marked and urgent need for such studies to ensure that the impacts of development programs across the range of intended and unintended sustainable development outcomes are quantified and considered when formulating policy. We address this gap by assessing how Brazil's flagship Zero Hunger (ZH) social protection programs have affected food production, multidimensional poverty, child malnutrition, infant mortality, and changes in natural vegetation cover. National development strategies frequently implement social protection programs to support livelihoods, alleviate income or food poverty, and manage vulnerability to shocks (11). Programs are often designed and evaluated as single instruments. A crucial part of any program evaluation is assessing whether program objectives are met, but programs rarely assess secondary outcomes that are not core objectives (12). This restricted focus increases the risk that trade-offs and perverse outcomes remain undetected, potentially generating incomplete conclusions on program effectiveness (13).

In our assessment of ZH's social protection programs, we leverage a suite of high spatial resolution datasets and use a quasi-experimental approach that combines covariate balancing weights with multiple regression analyses to help control for potential nonrandom program implementation. Our analysis provides insights on how to achieve multiple sustainability outcomes and is directly relevant to the design and implementation of social protection mechanisms in other regions of the world, particularly, sub-Saharan Africa where several programs are partly based on ZH (14).

Significance

Meeting SDGs requires assessing trade-offs and synergies across divergent goals and robust policy impact evaluation. Using quasi-experimental inference methods, we assess impacts of Brazil's Zero Hunger (ZH) social protection programs. ZH investment increased per capita calorie and protein productions. Social impacts (multidimensional poverty, child malnutrition, and infant mortality) were more limited, and the direction of change in natural vegetation cover was biome specific. Conditional cash transfer (BF) generated fewer benefits and more trade-offs than agricultural support (PRONAF). Results inform policy development, including roll out of ZH inspired programs in sub-Saharan Africa. We highlight successful elements of social protection programs, synergies, and trade-offs between multiple SDGs including environmental protection.

Author contributions: C.D., J.A.O., and K.L.E. designed research; C.D. performed research; C.D. analyzed data; and C.D., J.A.O., and K.L.E. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: cecidy85@gmail.com.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.1920998117/-/DCSupplemental.

First published August 11, 2020.

SUSTAINABILITY SCIENCE

Brazil's ZH Program

The ZH program aimed to lift 44 million poor Brazilians out of poverty and food insecurity and was fully implemented in 2004 (15). Four subprograms formed the core of ZH and, at its inception, received ~90% of ZH's total budget (15). ZH has since evolved into other initiatives (Brasil Sem Miseria, i.e., Brazil without extreme poverty) that continue to operate these four subprograms with national government funding allocated to state or municipal governments and, in some instances, directly to program beneficiaries. Small-scale family farmers are the programs' primary target beneficiaries due to their key role in rural development and national food security (16, 17). They are provided with: i) low interest agricultural credits through PRONAF and, ii) access to price-controlled markets through The Food Acquisition Program (PAA). The markets created through PAA are operated by state-linked institutions that buy produce directly from local farmers to supply social assistance programs, government funded school,s and local markets (15). A key social assistance program is iii) The National School Feeding Program (PNAE) which provides free school meals to all children and promotes the use of produce from family farms (15). Finally, families in poverty, many of which are small-scale farmers, qualify for monthly cash transfers through iv) the BF subprogram, conditional on child school attendance and participation in family health checks and vaccination programs (although families without children can also get support) (15). ZH and core subprograms predate the SDGs and do not combine objectives focused on protecting the natural environment or climate change mitigation with its objectives concerning food production and poverty. Nevertheless, these programs form an integrated large-scale initiative with the potential to influence both social and environmental dimensions captured in the SDGs framework, including rural livelihoods and food security, health outcomes, agricultural production, and land-use change. Assessing ZH and its contribution to multiple outcomes—both intended (food security, poverty, and health) and unintended (environmental)—is, thus, vital to get a full understanding of its contribution to transitions toward sustainability (10).

ZH programs have been associated with increased farm incomes and productivity (18–20), increases in agrobiodiversity (21), increased food purchases in food insecure households (22), reduced child malnutrition (23, 24), and lower infant mortality (25, 26). Yet, contrasting evidence suggests that ZH programs have had negligible effects on agricultural production, farmer livelihoods, child malnutrition, and long-term food security (27–30) and have failed to reach the poorest and most vulnerable families (31–33). However, the majority of ZH impact studies assess impacts on individual treated and untreated households. They, thus, focus exclusively on microscale pathways that generate benefits, ignoring the larger-scale indirect pathways through which benefits can accrue (e.g., impacts of market stimulation on untreated households, ref. 34). Assessing aggregate impacts over larger geographic scales enables us to: first—capture potential impacts arising from investment in ZH at the cost of reduced investment in other initiatives (e.g., basic infrastructure, ref. 35); and second—account for impacts of expansion of agricultural activities beyond the boundaries of household land parcels. Previous studies are also limited by a failure to consider spatial heterogeneities and/or key confounding factors and have focused on a narrow range of outcomes that prevent full exploration of synergies and trade-offs across multiple sustainable development objectives.

Analytical Approach

We assess ZH effects on food production, multidimensional poverty, health, and changes in natural vegetation cover using a quasi-experimental approach and municipal level publicly available data from national and global sources (see *Materials and Methods*). We created a high-spatial resolution longitudinal dataset for rural municipalities across Brazil (n = 3,786–4,976, i.e., 74–97% of all rural municipalities—sample sizes were outcome and program component dependent). We focus on rural areas because this is where family farmers (one of ZH's primary beneficiaries) are overwhelmingly concentrated and because impacts are likely to be heterogeneous across urban and rural areas. We first analyze the impact of summed financial investment across ZH's main subprograms (PRONAF, PAA, PNAE, and BF), and then separately assess the impacts of the two largest subprograms BF and PRONAF, which captured 46% and 42%, respectively, of ZH's summed investment between 2004 and 2013. These subprograms are examples of the types of social protection programs that are frequently implemented elsewhere: conditional cash transfer to protect minimum subsistence (BF) and credit provision to support household investment and livelihood diversification (PRONAF) (11).

We assess impact on changes in multidimensional poverty (SDG 1), food production (daily per capita kilocalorie and protein production; SDG 2), child malnutrition (proportion of underweight infants and children age 12–24 mo; SDGs 2 and 3), infant mortality (children <1 y; (SDGs 2 and 3), and area (km^2) under natural vegetation cover (SDGs 13 and 15). For all outcomes, we measure change from 2004 (the first complete year of ZH implementation) to 2013 (at the time of analysis, the most recent year with information across all predictor variables). We use two separate datasets for multidimensional poverty and infant mortality that represent: i) the poorest subsample of each municipality's population using data from the national primary information system (SIAB) (change assessed 2004–2013) (36), and ii) the entire municipal population using the national demographic census (due to census dates assessing change from 2000 to 2010).

We combine covariate balancing generalized propensity score weights (CBGPS method, ref. 37) with multiple regression analyses to assess links between investment and changes in outcomes. This helps limit potential nonrandom treatment allocation bias by reducing the correlation between treatment and potential confounding factors (37) (*Materials and Methods* and *SI Appendix, CBGPS*). We model outcomes in the final year of the evaluation period as a function of summed per capita investment in ZH (R$). We account for inflation (IGP-DI index, base year 2013), and control for 15 key biophysical and socioeconomic factors and baseline conditions, including variables that affect the implementation of ZH and its subprograms (*Materials and Methods* and *SI Appendix, Confounding variables* and Tables S1 and S2).

Our statistical regression models include interactions between investment and state or biome to account for potential spatial variation in program implementation and differential outcomes in divergent environments. We use our regression models to predict changes in outcomes resulting from three different investment scenarios: negligible investment (defined as the first percentile of investment values to avoid using zero values that would predict beyond the data range), actual investment, and a spatially uniform investment (defined as the median investment value). We map predicted percentage change in outcomes per municipality (arising from actual and spatially uniform investments) relative to a negligible investment scenario to visualize impacts across Brazil. We conduct several robustness tests to assess if our inferences still apply when excluding lower quality data—defined as municipalities with: i) extremely large areas (>10,000 km^2) that are likely to have less representative socioeconomic data (38), ii) SIAB data that do not meet quality criteria defined by the Ministry of Health (39), or iii) natural vegetation data that cover less than 95% of the municipality's area due to cloud cover in 2004 or 2013. Controlling for data quality in our natural vegetation robustness models leads to the exclusion of 77% and 99.7% of the Amazon and Pantanal biomes' area. We, therefore, exclude these biomes from our robustness tests. We focus on results from models that use all data when these are qualitatively similar to those from models that exclude lower quality data and, in the few cases where discrepancies arise, focus on results from the latter. We also check and confirm that our results are not unduly influenced by spatial autocorrelation or endogeneity (*Materials and Methods* and *SI Appendix*, *Robustness tests*).

Results

We find considerable heterogeneity in the effects of ZH investment. This variation arises for three primary reasons. First, impacts are outcome specific with evidence of positive, negligible, and negative effects. Second, within a single outcome, impacts depended on whether investment is delivered via conditional cash transfers (BF) or agricultural credits (PRONAF). Finally, within a single outcome variable and investment mechanism, there is often considerable spatial variation in the magnitude and direction of effects (Fig. 1). This is often not simply due to spatial variation in investment levels (*SI Appendix*, Fig. S1) as marked spatial variation in outcomes frequently remains when modeling outcomes using a spatially uniform investment level (*SI Appendix*, Fig. S2).

Food Production. Summed investment across ZH subprograms increased protein production across Brazil, while investment increased kilocalorie production in three states (Rondonia in the north, Sergipe in the northeast, and São Paulo in the southeast) and reduced in two (Acre in the north and Paraiba in the northeast) (Table 1 and Fig. 1). Substantial spatial variation in outcomes is partially driven by differing investment levels (*SI Appendix*, Fig. S1) as regional variation is reduced when keeping investment levels spatially uniform (Fig. 1 and *SI Appendix*, Fig. S2) as well as trade-offs between kilocalorie and protein productions arising primarily from BF investment.

Across most of Brazil, PRONAF investment was associated with increased protein (mean predicted change per municipality = 41.0%, SE = 0.9 compared to the negligible investment scenario; mean increase = 597.0 g per capita per day, SE = 25.7) and kilocalorie production (mean predicted change per municipality = 32.8%, SE = 0.9; mean increase = 37,668 kcal per capita per day, SE = 2,601). Although when excluding lower quality data investment only generated a significant increase in kilocalorie production in three states (Rondonia in the north, Bahia in the north-east, and São Paulo in the south-east) and investment significantly reduced production in four states (Acre and Para in the north, Paraiaba in the north-east, and Espirito Santo in the south-east). While percentage increases in production are more marked in southern Brazil (Fig. 1), this is linked to higher investment levels in this region (*SI Appendix*, Fig. S1): Using spatially uniform investment levels, PRONAF increases protein and kilocalorie productions in the north-east at a similar rate to the south, albeit from a lower base (*SI Appendix*, Fig. S2). This is notable as the north-east region has difficult climatic (hot and dry) and socioeconomic conditions and low productivity of family farms (40, 41). While family farmers in southern Brazil have participated more actively in larger national and international markets (42), e.g., for soybean, rice, and beef (43), family farmers in the north-east are generally poorer (42) but contribute greatly to local and national production of staple foods, such as rice, maize, and cassava (40). Diverting some PRONAF funds from the south to the north-east could, thus, deliver cost-effective national improvements in local food production targeted at regions with the greatest need and address a key critique that PRONAF favors wealthier farmers producing commodity products in the south (32).

BF also increased protein production (mean predicted change per municipality = 168.1%, SE = 8.8 per municipality; mean increase = 282.9 g per capita per day, SE = 20.0). Rates of increase appear to be greater in north-eastern states (e.g., Alagoas) where baseline production was low (Fig. 1) and food insecurity has been historically high (16). BF impacts probably arise because conditional cash transfer increases incomes in poor agricultural households by up to 46% (44). These can either facilitate investment in agricultural production (as observed for cash-transfer programs in Mexico, ref. 45) or stimulate food markets and increase local production due to increased purchasing power.

Despite positive BF effects on protein production, we find no overall effect of BF on kilocalorie production. We find, however, four states with BF-linked reductions in kilocalorie production (Amapa in the north, Bahia and Rio Grande do Norte in the north-east, and Goias in the center-west) and two states with BF-linked kilocalorie increases (Acre in the north and Rio Grande do Sul in the south; Fig. 1). These spatial patterns persist when modeling impacts using spatially uniform investments (*SI Appendix*, Fig. S2). One reason why BF investment may not have increased kilocalorie production may be that some farmers have used BF investment to switch from production of staple crops to protein production. To explore this potential mechanism, we assess rice and cassava productions (which are the main high kilocalorie crops) and milk and poultry productions (which are the main high-protein products generated by Brazilian small-scale farmers and used for local human consumption (16, 46). We find that total rice and cassava productions have declined by 45% in the north-east, 65% in the center-west, and 30% in the south-east. We also find that total milk and poultry productions increased in the north-east (milk = 26%; poultry = 14%), center-west (milk = 19%; poultry = 17%), and south-east (milk = 15%; poultry = 38%). Use of cash transfers to purchase rather than produce food is another potential mechanism for the declines in crop production (29, 30) especially when falling food prices (due to increases in agricultural productivity, primarily by large-scale agrobusinesses) increase purchasing power of money received through cash transfers especially for low income populations (47), while simultaneously reducing the profitability of small-scale production of staple crops. Regardless of the mechanism, BF does not seem to increase local production of stable crops, and, at worse, it may reduce it, which could reduce food security resilience to any future price shocks (2).

Multidimensional Poverty Index. We analyze two multidimensional poverty measures capturing information on living standards, health, and education. Our first measure uses data from the poorest subsample of the population (SIAB), while the second captures the municipality's entire population (census). SIAB derived multidimensional poverty is not associated with summed ZH investment across subprograms, and effects of PRONAF investment are negligible (Fig. 1 and *SI Appendix*, Table S3). BF investment is associated with increased SIAB derived multidimensional poverty (Table 1; mean predicted change per municipality = 80.7%, SE = 0.5; mean increase = 0.026 multidimensional poverty index [MPI], SE = 0.0003), however, when lower quality data are excluded, a significant increase in SIAB derived multidimensional poverty only remains in two states (Mato Grosso and São Paulo).

It is clear that BF has had limited capacity to alleviate multidimensional poverty and, in some regions, is associated with increased poverty—these findings are counter to expectations (25, 48), but our robustness tests strongly suggest that they do not arise due to hidden bias generated by unmeasured confounding factors (*SI Appendix*, *Robustness tests*). Indeed, previous studies suggest that, until 2010, BF support did not reach 1.2 million eligible families, and those that did receive support obtained insufficient funds to lift them out of poverty (44). Moreover, our results are compatible with a subnational case study showing that BF was associated with increased child malnutrition, which is part of our SIAB derived multidimensional poverty measure (27). Notably, BF support is conditional on child school attendance, and we do find that BF investment is associated with improvements in the educational dimension of our SIAB derived multidimensional

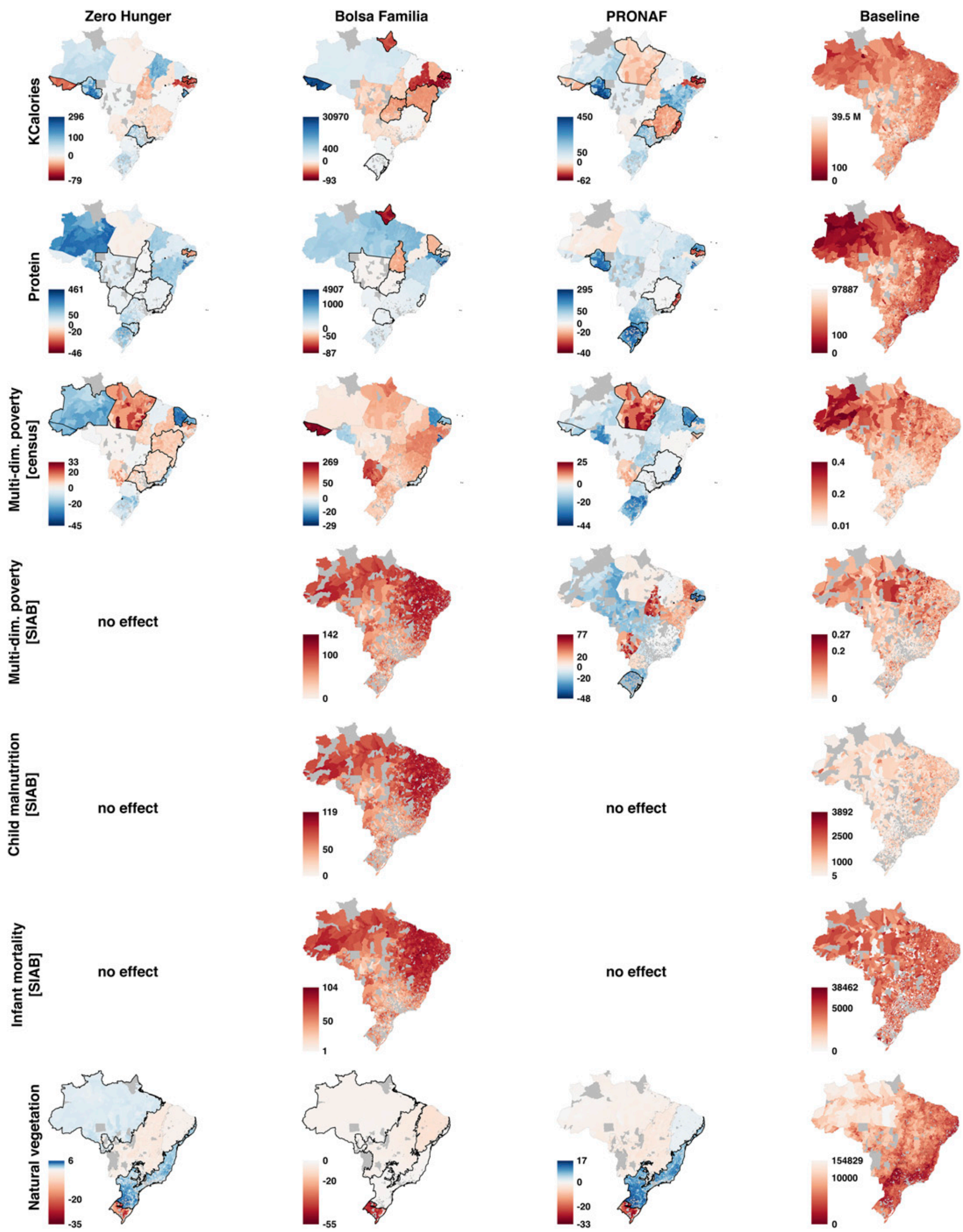

Fig. 1. Relative impact of ZH, BF, and PRONAF investments (columns 1–3) on daily per capita kilocalorie production, daily per capita protein production, multidimensional poverty in the entire population (census), multidimensional poverty in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors of society (SIAB), and natural vegetation cover (km^2). Relative impact is defined as the modeled change (percentage) in the outcome variable when investment increases from a spatially uniform negligible value (first percentile value) to the actual investment level. Column 4 shows outcome values at baseline (i.e., year 2000 for multidimensional poverty [census] and 2004 for all others). Relative impact calculations are based on robust multivariable regression models of a covariate-balanced sample (Table 1) that take confounding factors into account including interactions between investment and state, or biome (in the natural vegetation cover model). States and biomes with significantly different outcomes to the overall effect are indicated by thick black borders; thin black borders show region borders (rows 1–5) and ecological biome borders (row 6). We use a normative color scheme where, in columns 1–3, blue indicates beneficial impacts, and red indicates nonbeneficial impacts. In maps of baseline values (column 4) deeper red indicates municipalities with a worse starting condition, such as high multidimensional poverty or lower coverage of natural vegetation. Gray areas signify municipalities not included in the analysis because they were urban, have insufficient data, or fall within the model reference state or biome for which no model statistics are available.

poverty measure in two states (Parana and Santa Catarina: *SI Appendix*, Table S4). These positive impacts, while more limited, match those of previous research (49) and suggest that conditional cash transfers dependent on participation in education can support the educational targets of SDG 4.

There is little evidence that summed investment across ZH subprograms is associated with notable improvements in our census derived multidimensional poverty metric. While, when lower quality data are excluded, ZH investment is significantly associated with a multidimensional poverty reduction, the overall

Table 1. **Impacts of per capita summed ZH, BF, and PRONAF investments on food production, multidimensional poverty, child malnutrition, infant mortality, and natural vegetation cover from robust multivariable regression models of a covariate-balanced sample that take confounding factors into account**

	ZH				BF				PRONAF			
Outcome	Coef ± SE	P	Int.	R^2	Coef ± SE	P	Int.	R^2	Coef ± SE	P	Int.	R^2
Kilocalories (per capita)	0.002 ± 0.04	0.958	2×10^{-9}	0.93	−0.02 ± 0.02	0.454	1×10^{-17}	0.93	0.03 ± 0.01	0.005	2×10^{-54}	0.94
Protein (per capita)	0.08 ± 0.01	1×10^{-8}	1×10^{-25}	0.96	0.08 ± 0.02	5×10^{-6}	9×10^{-14}	0.96	0.04 ± 0.01	3×10^{-6}	6×10^{-76}	0.96
Multidim. poverty (census)	−0.01 ± 0.01	0.144	4×10^{-7}	0.77	0.05 ± 0.01	6×10^{-7}	0.001	0.79	−0.02 ± 0.004	1×10^{-6}	9×10^{-9}	0.77
Multidim. poverty (SIAB)	0.01 ± 0.01	0.380		0.61	0.08 ± 0.02	2×10^{-6}		0.61	0.002 ± 0.01	0.850	0.013	0.61
Child malnutrition (SIAB)	0.05 ± 0.04	0.192		n/a	0.18 ± 0.05	4×10^{-4}		n/a	−0.05 ± 0.03	0.099		n/a
Infant mortality (census)	0.01 ± 0.24	0.961		0.13	0.05 ± 0.22	0.805		0.14	−0.01 ± 0.24	0.976		0.14
Infant mortality (SIAB)	0.01 ± 0.04	0.777		n/a	0.16 ± 0.05	0.002		n/a	−0.02 ± 0.04	0.660		n/a
Natural veg. (km2)	−0.01 ± 0.004	9×10^{-5}	9×10^{-6}	0.99	−0.03 ± 0.01	9×10^{-5}	0.004	0.99	−0.01 ± 0.003	0.018	5×10^{-5}	0.99

Outcomes refer to daily per capita kilocalorie and protein production and multidimensional poverty in the entire population (census), and in the poorer sectors of society (SIAB), child malnutrition in the poorer sectors (SIAB) and infant mortality in the entire population (census), the poorer sectors (SIAB), and the area of natural vegetation. Model coefficients are reported ±one SE. Interaction terms (Int.) show *P* values for the interactions between investment and state in all models except the natural vegetation model in which the interaction is with biome type. When interaction terms are not significant, we report results from models that only contain main effects. State and biome have been encoded with deviation (effects) coding, thus, for models with an interaction, the main effects expressed here represent the average effect of investment across Brazil. Daily per capita kilocalorie and protein productions, multidimensional poverty (census), multidimensional poverty (SIAB), and area of natural vegetation are modeled using robust ordinary least squares (OLS), while infant mortality (census) is modeled using a negative binomial model, and infant mortality and child malnutrition (SIAB) are modeled with a quasi-Poisson model. Model r^2 for infant mortality (census) is calculated using McFaddens pseudo r^2 and is, thus, not comparable to those from OLS models. No pseudor^2 is available for quasi-Poisson models. All models have been adjusted to achieve covariate balance using the CBGPS method (19).

SUSTAINABILITY SCIENCE

effect is very small (mean predicted change = 1.9%, SE = 0.2 per municipality; mean reduction = 0.002 MPI, SE = 0.0001). When all data are included in the models, there is an approximate balance in the number of states with investment associated reductions in multidimensional poverty (five states: Acre and Amazonas in the north, Ceara and Rio Grande do Norte in the north-east, and Rio de Janeiro in the south-east) and poverty increases (four states: Para in the north, Bahia in the north-east, and Minas Gerais and São Paulo in the south-east; Fig. 1).

BF investment is generally associated with increases in census derived multidimensional poverty (mean predicted change = 34.7%, SE = 0.9 per municipality; mean increase = 0.013 MPI, SE = 0.0002 per municipality) and only one state exhibiting significant poverty alleviation in response to BF investment in both the core and the robust models (Fig. 1 and *SI Appendix*, *Robustness tests*). BF investment, however, is linked to significant improvements in the educational dimension of our census derived multidimensional poverty measure in some states (Para and Rondonia in the north and Alagoas and Bahia in the north-east: *SI Appendix*, Table S4).

Our results suggest that the effectiveness of BF on multidimensional aspects of poverty, other than educational benefits in some states, is constrained across much of Brazil. There are numerous possible mechanisms for this. First, supply-side constraints may play a role especially insufficient access to health services (50) and a lack of monitoring of the health and nutritional status of beneficiary families (e.g., between 2005 and 2012, 3.2 million BF households remained unmonitored, ref. 51). Notably these constraints have been reported to be less marked in north-eastern Brazil (52), which is where we find some evidence that BF alleviates (census derived) multidimensional poverty. Second, the increased taxation that is required to fund BF is disproportionately allocated to the poorer sectors of society, thus, increasing fiscal poverty among some BF participants (53) that reduces their capacity to purchase assets that contribute to our measure of multidimensional poverty. Finally, insufficient access to labor markets or longer-term financial security, e.g., through pensions, may also limit BF's ability to reduce multidimensional poverty (44).

In contrast to BF, we find that PRONAF investment was associated with an overall reduction in our census derived multidimensional poverty measure (Table 1; mean predicted change per municipality = 9.7%, SE = 0.2; mean reduction = 0.006 MPI, SE = 0.0001). The largest reductions, measured in terms of percentage change, occur in southern Brazil (22.2%, SE = 0.3) (Fig. 1). This is not due to higher investment as this spatial pattern remains under a uniform investment scenario (*SI Appendix*, Fig. S2) and is probably influenced by the lower census derived multidimensional poverty baselines in this region (Fig. 1), which increase rates of change expressed as percentages.

PRONAF funds must be invested in agricultural production. This investment could lead to increases in farm employment opportunities or stimulate labor markets associated with the production and sale of agricultural materials and equipment. Wealthier and more competitive farmers tend to be better placed than poorer farmers to benefit from any stimulation of labor markets (54), which might help explain the observed contrasting effects between the PRONAF associated improvements in census derived multidimensional poverty and the negligible effects in the SIAB derived multidimensional poverty measure.

Infant Mortality and Child Malnutrition. The only detected effect of ZH investment on infant mortality is that BF investment is associated with increased SIAB derived infant mortality (mean predicted change = 59.4%, SE = 0.4 per municipality; mean increase = 725.4 deaths per 100,000 live births, SE = 5.9 per municipality; Table 1). These effects were not detectable, however, when we exclude lower quality data (*SI Appendix*, Table S3). Increased child malnutrition for which data are only available from the poorest subsample (SIAB) is also associated with social security (BF) investment (mean predicted change = 67.7%, SE = 0.4 per municipality; mean increase = 103.4 underweight children per 10,000 weighed children, SE = 1.2 per municipality; Table 1).

In combination, our results provide strong evidence that investment in ZH programs is not alleviating SIAB derived child malnutrition, census, or SIAB derived infant mortality. Our findings extend earlier work conducted on local scales (27, 29, 50) to the national scale, although studies with beneficial associations between BF and child health also exist (25, 26). The lack of improvements in response to BF investment are compatible with and, may partly be driven by, higher multidimensional poverty levels and reduced per capita calorie production from staple crops, which we also find are associated with higher BF investment. Lack of improvements from BF investment may also be linked to insufficient monitoring and resultant intervention of the health and nutritional status of beneficiary families (see above), perhaps, due to diversion of funding away from municipal institutions in charge of monitoring (55) or investments in basic infrastructure (e.g., education, health centers, and public sanitation systems) (35, 56). Such infrastructure is still insufficient in many rural areas (57) and, particularly, among BF recipients (58) but is important for BF and conditional cash transfers to be effective (59). Similarly, the lack of beneficial impacts on child malnutrition and infant mortality arising from PRONAF investment occur despite PRONAF delivering substantial improvements in per capita food production.

This is unlikely a result of food unavailability due to export away from local markets since the share of family farm produce exported abroad is minimal (0.04% of temporary crops and 0.07% of permanent crops in 2006, ref. 60) and again probably arises due to poor access to health services and basic infrastructure for this sector of society and perhaps limited participation in PRONAF among poorer and more vulnerable farmers (32).

Natural Vegetation Cover. Summed investment across ZH subprograms is associated with increased natural vegetation cover in *the Amazon* (per municipality mean predicted change = 0.9%, SE = 0.01; mean predicted increase = 53.9 km^2, SE = 5.0; summed predicted increase = 24,434 km^2 across 454 municipalities), *Atlantic Forest* (per municipality mean predicted change = 2.4%, SE = 0.02; mean predicted increase = 2.5 km^2, SE = 0.1; summed predicted increase = 5,826 km^2 across 2,337 municipalities), and *Caatinga* (per municipality mean predicted change = 0.6%, SE = 0.003; mean predicted increase = 2.9 km^2, SE = 0.1; summed predicted increase = 2,210 km^2 across 772 municipalities, Caatinga predictions are from the model excluding lower quality data due to a change in the direction of effect compared to a model that uses all data irrespective of quality (Table 1, *SI Appendix*, Table S3, and Fig. 1). In contrast, summed ZH investment is associated with natural vegetation loss in the *Cerrado* (per municipality mean predicted change = 2.8%, SE = 0.04; mean loss = 30.9 km^2, SE = 1.6; summed predicted loss = 30,844 km^2 across 1,020 municipalities) and *Pampa* (per municipality mean predicted change = 19.9%, SE = 0.8; mean loss = 122.6 km^2, SE = 13.9; summed predicted loss = 11,155 km^2 across 92 municipalities).

The direction of the effect of PRONAF investment on natural vegetation cover was the same as impacts of summed investment (ZH) in all biomes except in the Amazon where PRONAF investment was associated with deforestation (mean predicted change = 1.6%, SE = 0.03 per municipality; mean decrease = 96.3 km^2, SE = 9.6 per municipality; summed predicted decrease = 42,863 km^2 across 454 municipalities). PRONAF investment was associated with natural vegetation gains in the *Atlantic Forest* (per municipality mean predicted change = 9.7%, SE = 0.1; mean increase = 9.7 km^2, SE = 0.3; summed predicted increase = 22,316 km^2 across 2,337 municipalities) and *Caatinga* (per municipality mean predicted change = 1.2%, SE = 0.01; mean increase = 5.5 km^2, SE = 0.2; summed predicted increase = 5,594 km^2 across 1,015 municipalities). In contrast, PRONAF investment was associated with natural vegetation losses in the *Cerrado* (per municipality mean predicted change = 3.0%, SE = 0.03; mean loss = 30.8 km^2, SE = 1.6; summed predicted loss = 31,030 km^2 across 1,020 municipalities) and *Pampa* (per municipality mean predicted change = 23.9, SE = 0.6; mean loss = 158.5 km^2, SE = 17.3; summed predicted loss = 14,427 km^2 across 92 municipalities). When the model excludes lower quality data (which means also excluding all of the Amazon and Pantanal biome), PRONAF loses its overall significant effect. The effect of investment in the Caatinga and Cerrado also become nonsignificant and is reduced to less than a 1% average predicted change, however, the significant gains of natural vegetation in the Atlantic Forest remains.

BF is associated with natural vegetation loss in four biomes: the *Amazon* (per municipality mean predicted change = 2.5%, SE = 0.02; mean loss = 181.9 km^2, SE = 18.3; summed predicted loss = 82,597 km^2 across 454 municipalities), the *Cerrado* (per municipality mean predicted change = 3.9%, SE = 0.04; mean loss = 45.0 km^2, SE = 2.3; summed predicted loss = 45,851 km^2 across 1,020 municipalities), *Atlantic Forest* (per municipality mean predicted change = 0.9%, SE = 0.01; mean predicted loss = 1.2 km^2, SE = 0.04; summed predicted loss = 2,660 km^2 across 2,337 municipalities), and *Pampa* (per municipality mean predicted change = 42.3%, SE = 0.6; mean loss = 377.2 km^2, SE = 41.2; summed predicted loss = 34,704 km^2 across 92 municipalities). In contrast, BF investment is associated with increased natural vegetation in the *Caatinga* (per municipality mean predicted change = 0.5%, SE = 0.001; mean predicted increase = 2.3 km^2, SE = 0.1; summed predicted increase = 1,743 km^2 across 772 municipalities, Caatinga predictions are from the model excluding lower quality data due to a change in the direction of effect compared to a model that uses all data irrespective of quality Table 1, *SI Appendix*, Table S3, and Fig. 1). Consequently, the contrast between negative impacts of PRONAF and BF on natural vegetation in the Amazon and apparent positive impacts of summed ZH investment suggest that the more minor ZH subprograms (i.e., PNAE and PAA) may drive positive forest transitions in the Amazon.

Our analyses focus on total change rather than fine-scale spatial dynamics of loss and gain but clearly indicate that social protection programs can have divergent and biome specific impacts on natural vegetation in biomes that support a number of endemic and globally threatened species. The Cerrado and Pampa biomes consistently lost natural vegetation as investment in summed ZH, PRONAF, and BF increased with proportional losses being particularly large in the Pampa. This conflicts with goals to maintain biodiversity (SDG 15). In other cases, investment was associated with increased natural vegetation cover, most notably, PRONAF investment was associated with increased Atlantic Forest vegetation—this and other changes in woody vegetation cover will influence carbon storage and sequestration (61) and, thus, action to tackle climate change (SDG 13). Investment in the heavily degraded and fragmented Atlantic Forest might have promoted agricultural intensification, limiting agricultural expansion, and enabling vegetation regrowth on more marginal lands. Investments in the Pampa and Cerrado, however, could have promoted agricultural expansion. Indeed, spatially explicit analyses across Brazil suggest that positive forest transitions in the Atlantic Forest are associated with agricultural intensification, while agricultural expansion has led to forest loss in the Cerrado (62). The greatest ZH associated losses of natural vegetation occur in the Pampa in which the flat terrain could have facilitated expansion of arable systems (soy and sugar cane) outside the flood plain as this is more profitable than the low-density livestock system that dominates the region (63) and driven by the loss of natural grassland—although expansion of livestock has also contributed to these losses (64). The expansion of arable crops is likely to be driven by demand from international commodity markets, which tend to drive land conversion as a result of improvements in production and profitability (2). Such agricultural expansion is likely to generate other losses of natural vegetation associated with investment in ZH, including PRONAF driven deforestation in the Amazon and BF-led vegetation losses across most of Brazil (i.e., all biomes except the Caatinga). Notably cash-transfer programs focusing on poverty alleviation have been linked to deforestation elsewhere in the Neotropics because they promote the consumption of products that require large areas of land for their production (65).

Discussion and Policy Recommendations

Our analysis of ZH's social protection programs reveals synergies and trade-offs across outcomes and program components. We show that increases in food production (linked to the food availability aspect of food security—SDG 2) do not lead to improvements in other food security and health measures (child malnutrition and infant mortality—SDGs 2 and 3). Multidimensional poverty reductions (SDG 1), when present, are modest especially for the poorer sectors of society. ZH's social protection programs have also had substantial effects on natural vegetation cover (SDGs 13 and15). Notably, the direction of these impacts vary across biomes, which is probably linked to regional differences in the capacity for investment to limit agricultural expansion and associated forest transitions. It is clear, however, when considering all outcomes, that positive synergies (win–win outcomes) across divergent sustainable development goals arose more rarely than trade-offs (win–lose) and negative synergies (lose–lose) as a consequence of investment in social protection programs (Table 1; see Fig. 2 for examples). Notably positive synergies can arise across paired outcomes relating to human well being and environmental protection (Fig. 2). This is of notable policy relevance as environmental outcomes of social protection programs are much less well understood than their impacts on people (13).

Several factors could have increased the probability that benefits of social protection programs are either limited or trade off against additional sustainable development objectives. Access to ZH's social security programs in Brazil has not been conditional on environmental compliance–this contrasts with the Brazilian Central Bank's policy (Resolution 3,545) where rural credit conditioned on proof of environmental land registration has reduced deforestation rates in the Amazon (66). Environmental conditionalities imposed on social protection programs that encourage retention of natural vegetation on land holdings, while promoting farming practices that can increase yields on cultivated/grazed areas could help mitigate the trade-offs between protecting natural vegetation and food production objectives that we document. Such conditionalities would need to be coupled with mechanisms, such as agricultural extension assistance, to ensure that poorer and disadvantaged farmers (e.g., those with small land areas) are able to comply and are not discouraged from accessing social security programs. These conditionalities will not, however, curb negative environmental effects from nonrecipient farmers who respond to program induced stimulation of local markets.

Conditional cash transfers (BF) are associated with improved educational metrics in a few states, but they have had limited effectiveness in alleviating multidimensional poverty and health benefits (a key dimension of poverty). This seems likely to have been primarily driven by a diversion of funds to cash transfers and away from the institutions and infrastructure that are also needed to deliver health improvements (35, 55, 56). Reversing this change is likely to be costly but beneficial in delivering target outcomes. Conditioning receipts of benefits on maintaining some production of staple crops could also limit a shift away from staple crop production, which has probably also contributed to limited alleviation of multidimensional poverty and health outcomes, and increase family farmers' resilience against price shocks.

National and local contexts need to be considered when social protection programs are designed, implemented, and evaluated. Our analyses can, however, inform discussion of the ZH inspired social protection programs that currently operate in sub-Saharan Africa, (e.g., conditional cash transfers in Ghana, ref. 67, purchase from Africa for Africans [PAA Africa] in Ethiopia, Malawi, Mozambique, Niger, and Senegal, ref. 68, and rural credit in Zimbabwe, ref. 69). Crop yields in these regions are typically stagnant and are even falling in some locations against a background of rapid rises in demand due to human population growth rates (70). Experimental and theoretical evidences, however, strongly indicate the potential for changes in agricultural practice to close yield gaps across much of sub-Saharan Africa and meet increasing demand when combined with additional intensification measures including irrigation and increased cropping frequency (71). Targeting poverty through improving market access and

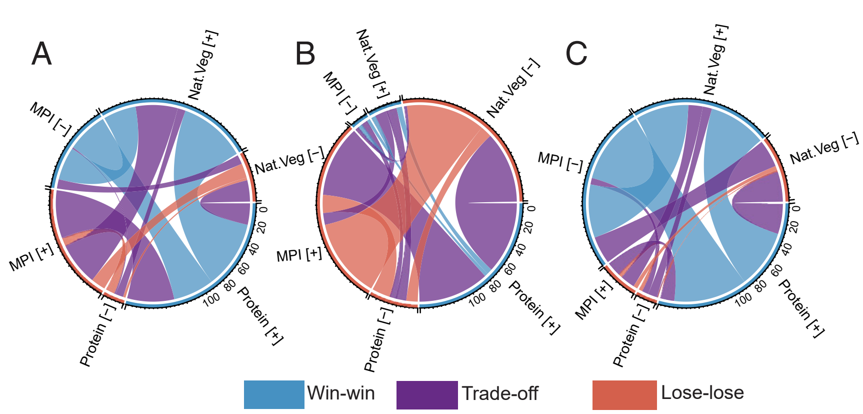

Fig. 2. Positive synergies (win–wins), trade-offs (win–lose), and negative synergies (lose–lose) from (*A*) ZH, (*B*) BF, and (*C*) PRONAF investments across three examples of sustainability outcomes, i.e., changes in per capita protein production (SDG 2), multidimensional poverty (census; SDG 1), and natural vegetation (SDGs 13 and 15). These have been selected as examples of key outcomes related to divergent SDGs. Colored bands indicate the type of relationship (positive synergies [win–win], negative synergies [lose–lose], or trade-offs) between outcome variables; with the thickness of each link representing the percentage of municipalities that exhibit each type of relationship for each pair of outcome variables (indicated by the scale bar on the edge of each circle). Impact of program outcomes is calculated from robust multivariable regression models of a covariate-balanced sample (Table 1; n = 4,663–4,924 municipalities depending on the outcome pairings).

off-farm opportunities will also make substantial contributions to increasing food security in sub-Saharan Africa (72). ZH derived social protection programs that simultaneously tackle poverty and food production are, thus, well placed to contribute to tackling the region's food insecurity. This is also likely to generate health outcomes as food insecurity is a major contributor to poor health in sub-Saharan Africa (5). Our results highlight a number of factors that are likely to enhance the success of ZH inspired programs in sub-Saharan Africa and reduce trade-offs with other SDGs. Program effectiveness is likely to be particularly influenced by associated investment in health infrastructure and improved functioning of institutions, including site specific agricultural extension offices (73, 74), which are often limited in rural areas of sub-Saharan Africa (11, 75). Despite the potential to improve food production without requiring agricultural expansion that trades off against protecting natural vegetation and associated biodiversity and carbon stocks, avoidance of such negative synergies is likely to require including environmental conditionalities in social protection programs. This will also require supporting agricultural extension offices to advice on environmental aspects and institutional capacity to monitor compliance. Regular fine-scale monitoring and evaluations of interventions that consider social, economic, and biophysical heterogeneity will also enhance outcomes by suggesting pathways toward program improvement during implementation cycles.

While our analyses reveal that investment in ZH may have been less successful in meeting some of its objectives than indicated by previous analyses, we provide nation-wide evidence that investment has benefited food production and, in some regions, has additionally benefited multidimensional poverty and natural vegetation, particularly, from interventions providing rural credit to family farmers. Recent political changes in Brazil have led to substantial budget cuts for core subprograms assessed in this paper (76). Our analyses indicate that these policy changes may halt or even reverse advances that Brazil has made toward increasing food availability (SDG 2), reducing poverty (SDG 1), and conserving natural vegetation and its associated benefits (SDGs 13 and 15).

Materials and Methods

Our analysis relies on a longitudinal dataset spanning the period between 2000 and 2013 and covering between 3,786 and 4,976 rural municipalities in Brazil. This dataset is constructed from publicly available national and global datasets. Our identification strategy leverages heterogeneity in investment levels in ZH and its core subprograms (BF and PRONAF) to assess how social protection programs influence a range of key indicators linked to multiple sustainable development outcomes: multidimensional poverty (SDG 1), food security (SDG 2), health (SDG 3), and natural vegetation changes (relating to action to tackle climate change SDG 13 and SDG 15). We conduct all our calculations in R version 3.4.2 (77) and improve the causal inference of our analysis by using a quasi-experimental design. This design uses a suite of 15 key biophysical and socioeconomic variables to control for potential factors affecting ZH investment and our outcomes of interest and to generate a series of covariate balancing generalized propensity score weights. We also conduct a series of robustness tests to verify that our results are not unduly influenced by data quality, spatial autocorrelation, and endogeneity. Please refer to the Supplementary Information for a detailed description of our methods, including: i) the construction of indicators, treatment variables, covariates, and respective data sources; ii) information on our regression model specifications and quasi-experimental design; and iii) robustness tests.

Data Availability. The data and analysis code have been deposited in the Harvard Dataverse, https://doi.org/10.7910/DVN/RLEPZ5 (78).

ACKNOWLEDGMENTS. We thank Tim Benton and Armando Barrientos for thoughtful comments on earlier versions of this paper. This work was supported by the Grantham Centre for Sustainable Futures at the University of Sheffield. The findings and conclusions expressed are solely those of the authors and do not represent the views of the Grantham Centre for Sustainable Futures or any other involved parties.

1. J. Loos *et al*., Putting meaning back into "sustainable intensification.". *Front. Ecol. Environ.* **12**, 356–361 (2014).
2. P. Meyfroidt, Trade-offs between environment and livelihoods: Bridging the global land use and food security discussions. *Glob. Food Secur.* **16**, 9–16 (2018).
3. United Nations, "The 17 goals." https://sdgs.un.org/goals. Accessed 18 September 2019.
4. FAO, IFAD, UNICEF, WFP, WHO, *The State of Food Security and Nutrition in the World. Building Resilience for Peace and Food Security*, (FAO, Rome, 2017).
5. J. Ingram, A food systems approach to researching food security and its interactions with global environmental change. *Food Secur.* **3**, 417–431 (2011).
6. T. Benton, The many faces of food security. *Int. Aff.* **92**, 1505–1515 (2016).
7. F. N. Tubiello *et al*., The contribution of agriculture, forestry and other land use activities to global warming, 1990-2012. *Glob. Change Biol.* **21**, 2655–2660 (2015).
8. T. Newbold *et al*., Global effects of land use on local terrestrial biodiversity. *Nature* **520**, 45–50 (2015).
9. M. Nilsson, D. Griggs, M. Visbeck, Policy: Map the interactions between Sustainable Development Goals. *Nature* **534**, 320–322 (2016).
10. F. Alpízar, P. J. Ferraro, The environmental effects of poverty programs and the poverty effects of environmental programs : The missing RCTs. *World Dev.* **127**, 2019–2021 (2020).
11. S. Devereux, Social protection for enhanced food security in sub-Saharan Africa. *Food Pol.* **60**, 52–62 (2016).
12. A. Barrientos, Social transfers and growth : What do we know? What do we need to find out? *World Dev.* **40**, 11–20 (2012).
13. C. Liao, D. G. Brown, Assessments of synergistic outcomes from sustainable intensification of agriculture need to include smallholder livelihoods with food production and ecosystem services. *Curr. Opin. Environ. Sustain.* **32**, 53–59 (2018).
14. M. Fraundorfer, Zero hunger for the world: Brazil's global diffusion of its Zero Hunger strategy. *Austral Braz. J. Strateg. Int. Relat.* **2**, 91–116 (2013).
15. J. G. da Silva, M. E. Del Grossi, C. G. de França, *The Fome Zero (Zero Hunger) Program: The Brazilian Experience*, J. G. da Silva, M. E. Del Grossi, C. G. de França, Eds. (MDA, Brasília, 2010), pp. 1–360.
16. A. W. Kepple, A. Carolina, F. Silva, E. A. Fernandes, *The State of Food and Nutrition Security in Brazil: A Multi-Dimensional Portrait*, (FAO, Brasília, 2014).
17. L. H. Samberg, J. S. Gerber, N. Ramankutty, M. Herrero, P. C. West, Subnational distribution of average farm size and smallholder contributions to global food production. *Environ. Res. Lett.* **11**, 1–11 (2016).
18. M. Doretto, E. Michellon, "Avaliação dos Impactos Econômicos, Sociais e Culturais do Programa de Aquisição de Alimentos no Paraná" in *Avaliação de Políticas de Aquisição de Alimentos*, F. B. B. Filho, A. D. de Carvalho, Eds. (UnB/CEAM/NER, ed. 27, 2007), pp. 107–138.
19. F. Garcia, S. M. Helfand, A. P. Souza, "Conditional cash transfers and rural development policies in Brazil: Exploring potential synergies between Bolsa Família and PRONAF." https://www.semanticscholar.org/paper/Conditional-Cash-Transfers-and-Rural-Development-in-Garc%C3%ADa-Helfand/bb30d82adaabc5ee63-d6ae644fb5aa1522ade1fbb. Accessed 18 September 2019.
20. M. de O. Garcias, A. L. Kassouf, Assessment of rural credit impact on land and labor productivity for Brazilian family farmers. *Nova Econ.* **26**, 721–746 (2016).
21. V. Valencia, H. Wittman, J. Blesh, Structuring markets for resilient farming systems. *Agron. Sustain. Dev.* **39**, 1–14 (2019).
22. IBASE Agência, *Repercussões do Programa Bolsa Família na Segurança Alimentar e Nutricional das Familias Beneficiadas*, (IBASE, Rio de Janeiro, 2008).
23. A. de Brauw, D. O. Gilligan, J. Hoddinott, S. Roy, *The Impact of Bolsa Familia on Child, Maternal, and Household Welfare*, (IFPRI, Washington, D.C., 2012).
24. R. Paes-Sousa, L. M. P. Santos, É. S. Miazaki, Effects of a conditional cash transfer programme on child nutrition in Brazil. *Bull. World Health Organ.* **89**, 496–503 (2011).
25. D. Rasella, R. Aquino, C. A. Santos, R. Paes-Sousa, M. L. Barreto, Effect of a conditional cash transfer programme on childhood mortality: A nationwide analysis of Brazilian municipalities. *Lancet* **382**, 57–64 (2013).
26. E. S. A. D. Silva, N. A. Paes, Bolsa Família Programme and the reduction of child mortality in the municipalities of the Brazilian semiarid region. *Cien. Saude Colet.* **24**, 623–630 (2019).
27. J. A. Labrecque *et al*., Effect of a conditional cash transfer program on length-for-age and weight-for-age in Brazilian infants at 24 months using doubly-robust, targeted estimation. *Soc. Sci. Med.* **211**, 9–15 (2018).
28. J. A. Oldekop *et al*., Linking Brazil's food security policies to agricultural change. *Food Secur.* **7**, 779–793 (2015).
29. B. A. Piperata, K. McSweeney, R. S. Murrieta, Conditional cash transfers, food security, and health: Biocultural insights for poverty-alleviation policy from the Brazilian Amazon. *Curr. Anthropol.* **57**, 806–826 (2016).
30. K. Thorkildsen, Social-ecological changes in a Quilombola community in the Atlantic forest of Southeastern Brazil. *Hum. Ecol. Interdiscip. J.* **42**, 913–927 (2014).
31. R. Paes-Sousa, J. Vaitsman, The Zero Hunger and Brazil without extreme poverty programs: A step forward in Brazilian social protection policy. *Cien. Saude Colet.* **19**, 4351–4360 (2014).
32. F. G. Silveira *et al*., *Public Policies for Rural Development and Combating Poverty in Rural Areas*, (IPC-IG, Brasília, 2016).
33. A. Soares *et al*., *Structured Demand and Smallholder Farmers in Brazil: The Case of PAA and PNAE*, (UNDP-IPC, Brasília, 2013).

34. OECD, *Can Social Protection Be an Engine for Inclusive Growth?*, Development Centre Studies, Ed. (OECD Publishing, 2019).
35. A. Hall, Brazil's Bolsa Familia : A double-edged sword? *Dev. Change* **39**, 799–822 (2008).
36. D. Rasella, R. Aquino, M. L. Barreto, Impact of the Family Health Program on the quality of vital information and reduction of child unattended deaths in Brazil: An ecological longitudinal study. *BMC Public Health* **10**, 380 (2010).
37. C. Fong, C. Hazlett, K. Imai, Covariate balancing propensity score for a continuous treatment: Application to the efficacy of political advertisements. *Ann. Appl. Stat.* **12**, 156–177 (2018).
38. D. I. Gregorio, L. M. Dechello, H. Samociuk, M. Kulldorff, Lumping or splitting: Seeking the preferred areal unit for health geography studies. *Int. J. Health Geogr.* **4**, 6 (2005).
39. Ministerio da Saude, *Sistema de Informação da Atenção Básica SIAB Indicadores 2002*, (Ministerio da Sauda, Brasília, 2003).
40. C. E. Guanziroli, A. Marcio, A. Di Sabbato, Dez Anos de Evolução da Agricultura Familiar no Brasil : (1996 e 2006). *Rev. Econ. Sociol. Rural* **50**, 351–370 (2012).
41. D. Sietz *et al*., Smallholder agriculture in Northeast Brazil: Assessing heterogeneous human-environmental dynamics. *Reg. Environ. Change* **6**, 132–146 (2006).
42. L. Cabral, A. Favareto, L. Mukwereza, K. Amanor, Brazil's agricultural politics in Africa: More food international and the disputed meanings of "family farming.". *World Dev.* **81**, 47–60 (2016).
43. T. E. de Oliveira *et al*., Agricultural land use change in the Brazilian Pampa Biome: The reduction of natural grasslands. *Land Use Policy* **63**, 394–400 (2017).
44. R. G. Osorio, P. H. G. F. de Souza, S. S. D. Soares, L. F. B. de Oliveira, *Perfil da Pobreza no Brasil e sua Evolução no Período 2004-2009*, (IPEA, Brasília, 2011).
45. J. E. Todd, P. C. Winters, T. Hertz, Conditional cash transfers and agricultural production: Lessons from the oportunidades experience in Mexico. *J. Dev. Stud.* **46**, 39–67 (2010).
46. J. L. P. Daniel, T. F. Bernardes, C. C. Jobim, P. Schmidt, L. G. Nussio, Production and utilization of silages in tropical areas with focus on Brazil. *Grass Forage Sci.* **74**, 188–200 (2019).
47. D. Arias, P. A. Vieira, E. Contini, B. Farinelli, M. Morris, *Agriculture Productivity Growth in Brazil: Recent Trends and Future Prospects*, (World Bank Group, Washington, D.C., 2017).
48. K. Lindert, A. Linder, J. Hobbs, B. de la Brière, *The Nuts and Bolts of Brazil's Bolsa Família Program: Implementing Conditional Cash Transfers in a Decentralized Context*, (The World Bank, Washington, D.C., 2007).
49. A. de Brauw, D. O. Gilligan, J. Hoddinott, S. Roy, The impact of Bolsa Família on schooling. *World Dev.* **70**, 303–316 (2015).
50. F. V. Soares, R. P. Ribas, R. G. Osorio, Evaluating the Impact of Brazil's Bolsa Familia: Cash transfer programs in comparative perspective. *Lat. Am. Res. Rev.* **45**, 173–190 (2010).
51. T. Cambello, M. C. Neri, *Bolsa Familia Program: A Decade of Social Inclusion in Brazil: Executive Summary*, T. Campello, M. Côrtes Neri, Eds. (MDS and IPEA, 2014).
52. F. R. de Araújo, M. A. D. de Araújo, F. J. V. de Souza, I. L. P. Gurgel, A. C. C. Gomes, Distribuição Espacial do Desempenho do Programa Bolsa Família: Um Estudo à Luz do IGD-M. *Rev. Ciencias Sociais, Rio Janeiro* **61**, 773–806 (2018).
53. S. Higgins, N. Lustig, Can a poverty-reducing and progressive tax and transfer system hurt the poor? *J. Dev. Econ.* **122**, 63–75 (2016).
54. S. M. Helfand, A. R. B. Moreira, E. W. Bresnyan Jr, "Agricultural productivity and family farms in Brazil: Creating opportunities and closing gaps." https://economics.ucr.edu/docs/helfand/Helfand%20Ag%20Productivity%20and%20Family%20Farms%20in%20Brazil%202015.pdf. Accessed 18 September 2019.
55. W. Hunter, N. B. Sugiyama, "Assessing the Bolsa Familia: Successes, shortcomings, and unknowns" in *Democratic Brazil Divided*, P. R. Kingstone, T. J. Power, Eds. (University of Pittsburgh Press, 2017), pp. 131–151.
56. D. Sánchez-Ancochea, L. Mattei, Bolsa Família, poverty and inequality: Political and economic effects in the short and long run. *Glob. Soc. Policy* **11**, 299–318 (2011).
57. S. Soares, L. De Souza, W. J. Silva, F. G. Silveira, *Poverty Profile: The Rural North and Northeast Regions of Brazil*, (IPC-IG, Brasília, 2016).
58. C. F. Camargo, C. R. B. Curralero, E. C. Licio, J. Mostafa, "Perfil socioeconômico dos beneficiários do programa Bolsa Família: O que o cadastro único revela?" in *Programa Bolsa Família: Uma Década de Inclusão e Cidadania*, T. Campello, M. C. Neri, Eds. (IPEA, 2013), pp. 1–494.
59. S. Cecchini, A. Madriaga, *Conditional Cash Transfer Programmes: The Recent Experience in Latin America and the Carribbean*, (United Nations, Santiago, 2011).
60. S. Schneider, A. Cassol, *"A Agricultura Familiar no Brasil". Serie Documentos de Trabajo N° 145. Grupo de Trabajo: Desarrollo con Cohesión Territorial*, (Programa Cohesión Territorial para el Desarrollo, Santiago, 2013).
61. C. Y. Shimamoto, P. C. Botosso, M. C. M. Marques, Forest Ecology and Management How much carbon is sequestered during the restoration of tropical forests? Estimates from tree species in the Brazilian Atlantic forest. *For. Ecol. Manage.* **329**, 1–9 (2014).
62. A. G. O. P. Barretto, G. Berndes, G. Sparovek, S. Wirsenius, Agricultural intensification in Brazil and its effects on land-use patterns: An analysis of the 1975-2006 period. *Glob. Change Biol.* **19**, 1804–1815 (2013).
63. A. E. Arantes, V. R. de M. Couto, E. E. Sano, L. G. Ferreira, Livestock intensification potential in Brazil based on agricultural census and satellite data analysis. *Pesqui. Agropecu. Bras.* **53**, 1053–1060 (2018).
64. P. Modernel *et al*., Land use change and ecosystem service provision in Pampas and Campos grasslands of southern South America. *Environ. Res. Lett.* **11**, 1–22 (2016).
65. J. Alix-Garcia, C. Mcintosh, K. R. E. Sims, J. R. Welch, The ecological footprint of poverty allevation: Evidence from Mexico's oportunidades program. *Rev. Econ. Stat.* **95**, 417–435 (2013).
66. J. Assunção, C. Gandour, R. Rocha, R. Rocha, *The Effect of Rural Credit on Deforestation : Evidence from the Brazilian Amazon*, (Climate Policy Initiative, Rio de Janeiro, 2016).
67. I. Costa-Leite, B. Suyama, M. Pomeroy, *Africa-Brazil Co-Operation in Social Protection Drivers, Lessons and Shifts in the Engagement of the Brazilian Ministry of Social Development*, (UNU-WIDER, Helsinki, 2013).
68. C. Milhorance, M. Bursztyn, E. Sabourin, The politics of the internationalisation of Brazil's "Zero Hunger" instruments. *Food Secur.* **11**, 447–460 (2019).
69. F. M. Pierri, How Brazil's agrarian dynamics shape development cooperation in Africa. *IDS Bull.* **44**, 69–79 (2013).
70. D. K. Ray, N. Ramankutty, N. D. Mueller, P. C. West, J. A. Foley, Recent patterns of crop yield growth and stagnation. *Nat. Commun.* **3**, 1293 (2012).
71. M. K. van Ittersum *et al*., Can sub-Saharan Africa feed itself? *Proc. Natl. Acad. Sci. U.S.A.* **113**, 14964–14969 (2016).
72. R. Frelat *et al*., Drivers of household food availability in sub-Saharan Africa based on big data from small farms. *Proc. Natl. Acad. Sci. U.S.A.* **113**, 458–463 (2016).
73. C. Ragasa, J. Mazunda, The impact of agricultural extension services in the context of a heavily subsidized input system: The case of Malawi. *World Dev.* **105**, 25–47 (2018).
74. O. Oyinbo *et al*., Farmers' preferences for high-input agriculture supported by site-specific extension services: Evidence from a choice experiment in Nigeria. *Agric. Syst.* **173**, 12–26 (2019).
75. A. R. Dorward, J. F. Kirsten, S. W. Omamo, C. Poulton, N. Vink, "Institutions and the agricultural development challenge in Africa" in *Institutional Economics Perspective on African Agricultural Development*, (IFPRI, 2009), pp. 1–34.
76. K. Doniec, R. Dall'Alba, L. King, Brazil's health catastrophe in the making. *Lancet* **392**, 731–732 (2018).
77. R Core Development Team, *R: A Language Environment for Statistical Computing*, (R Foundation for Statistical Computing, 2018).
78. C. Dyngeland, Brazil zero hunger: Data and code. Harvard Dataverse, V1. https://doi.org/10.7910/DVN/RLEPZ5. Deposited 31 July 2020.