We thank all referees for the careful and positive reviews and comments. Kindly find in the following the point by point responses by the authors to referees' comments and notes and further improvements of the manuscript, accompanying tillage dataset and corresponding R-code (now version 1.1).

Referee comments:	Author's responses	Improved text
Referee #1		
Comment on line 266: the Pittelkow data are not reliable source, since they are derived from a metanalysis of not accurate data; practical field experiences particularly in rice, but also in some root and tuber crops (cassava, portato) show same or higher yields under no till and no puddling.	Thank you for pointing out this uncertainty in assumptions made building on data of Pittelkow et al. (2015). We improved our statement in the text, first by shifting the paragraph to the section 2.4.1 describing the concrete CA area downscaling to avoid confusion on the mapping rules described in the other tillage system area derivation.	All annual rainfed root, tuber, and rice cropland is excluded from the potential CA area following Pittelkow et al. (2015), who reported larger yield penalties for these crop types when applying no-tillage practices. Rice is often produced as paddy rice, requiring puddling, which is a practice modifying the soil aggregates a lot in order to facilitate the flooded condition, e.g. to suppress weed growth. A conversion from puddled to dryland rice production as well as improved drainage of tuber crops production area may require additional management steps by the farmer in order to achieve comparable yield levels with no-tillage as under conventional production methods.
In general the wording "land suitable for CA" should be changed. There is no land which is not suitable for sustainable farming, but those land areas referred to as suitable might be more likely for adoption of CA while other land or crop areas might require more assistance or support for adoption.	We support your argument that theoretically all croplands can be farmed in a sustainable way. In the manuscript and R-script we now changed 'land suitable for CA' and 'potentially CA-suitable area' to 'potential CA area' as wordings also used in Prestele et al. (2018) and 'scenario CA area' respectively.	Entire manuscript
Referee #2		
The paper would be improved if the "bigger picture" was considered. In the discussion the authors discuss the impact of the work and the use the dataset could be put to but it would be an improvement to see this in the abstract and introduction. If you want the readers to use the data then you need to promote its uses as early as possible.	Thank you for this suggestion. We revised the abstract by already there emphasizing the possible applications and significance of the tillage data set for impact assessment of soil management practices on carbon, water, and nutrient cycling.	Abstract

Section 5 "Data Availability" needs expanding. Although you provide links to the data repository it would be an improvement to give some details of the structure of the data files. You seem to be using netCDF but it is worthwhile telling the reader the "flavour" of the format: are you using netCDF3, netCDF4 netCDF4 - classic for example. The other point is are these file CF compliant and if so which standard you are working to It is always useful to the potential user to know what meta data (global attributes) are in the files and if the file naming structure has any useful information embedded in it. It's also useful to provide the reader with an indication of what variables are in the filesetc. The final point is about the user license and if the data set has a DOI.	We have now extended the data availability section with additional technical details. The user may also refer to more details described on the website and accompanying meta-data of the repository where the code and data set are available for download	The presented tillage system dataset and source code are available under the ODBL (data) and MIT (source code) licenses. The tillage dataset can be downloaded from: http://doi.org/10.5880/PIK.2019.009 and the corresponding R-code from: http://doi.org/10.5880/PIK.2019.010. The dataset is provided in netCDF format (version 4) and consists of 42 layers each reporting crop-specific tillage systems per grid cell. Additionally, we provide a layer indicating area, where adoption of Conservation Agriculture could be facilitated (scenario CA area). The dataset can be used as a direct input, be applied as a mask or overlay for identifying tillage area. The R-code is provided to increase transparency of our methods but also to enable other modelling groups to adjust our tillage area mapping algorithm to their needs, e.g. for different input data or scenarios. Supplementary information (SI) is available in the online version of this article.
Technical corrections Table 1: increase column width to allow "Conservation" to appear on one line	We agree and did so.	
Table 5: Increase column width to make "Logit-ref\and k-50%" to appear as "Logit-ref and\k-50%" - make the column title structure consistent between columns	We agree and did so.	
Tables general: consider using central justification as it will improve the appearance.	We agree and did so.	
Line 221: Sentence "We developed several rules have been in order.." does not make sense.	We agree and revised the sentence.	We developed several rules in order to allocate the derived tillage systems to the grid scale.
Line 225: Replace "to" with "of"	Maybe there is a misunderstanding but we improved the sentence by deleting the ending "s" in "units".	…to distribute data of a larger spatial unit to the grid cell level…

Line 262: Change "most efficient and homogeous" to "more efficiently and homogeneously"	We agree and revised the sentence.	…because efficient and equal distribution of water requires some leveling off of the field to flatten the surface in order to distribute irrigation water more efficiently and homogeneously over the field.
Line 297: Change "few" to "low"	We agree and did so.	
Line 454: Change "It is" to "It has"	We agree and did so.	
Line 455: Change to "South of the Sahal region"	We agree and revised the sentence.	It occurs in Mexico, South of the Sahel region but mostly is found on cropland in India (Table S8 for further metrics across tillage system areas; Table S9).
Figure 1: The diagram is ok as it stands but would be much improved is standard flowchart practices were followed and the "yes\no" decisions were added to the relevant lines.	We adjusted slightly the settings of the flow chart but refrained from adjusting for exact flow chart standard as diamond shape for processes (decisions) would require more space than our chosen rectangle shape but we add the "yes\no" decisions to the relevant lines and updated figure 1 in the manuscript.	Figure 1
Referee #3		
My main concern is that the authors have used a series of assumptions and simplified rules to produce their deterministic dataset. However, they haven't acknowledged the uncertainties derived from this process. How confident the user can be in the categories assigned to each cell? **I understand that a partial or full verification is not feasible due to the lack of verification data. As the authors mention, the figures/table in S11 can't be considered as a verification as there is a mismatch in the dates. However, the results do suggest that there can be large errors locally.**	Our mapping rules are generated on the basis of literature findings on globally relevant tillage types, their underlying reasons, and purposes. In the absence of any statistical data for soil management at the global scale (except for Conservation Agriculture (CA) practices), we use proxy relations and data which can indicate tillage types of relevant difference but representative enough for existing cropping systems. We are aware that the use of proxy data and an area prioritization based on simple rules cannot reproduce the spatial patterns of actual tillage systems but rather should be seen as an approximation to reality making best use of available knowledge and data. The comparisons to other data illustrate that mayor spatial patterns can be reproduced but as you mentioned locally errors might be large. We have extended the	Section 4.2

	discussion of these points in section 4.2, making clear that the data set presents a scenario of current conditions that is based on plausible combinations of best knowledge and data.	
Also, there is no mention of uncertainties in the input dataset used (point 2.2.). How reliable are the input datasets used and how is this going to influence the output dataset?	Indeed, each input data set comes with its own uncertainties, which is often not described explicitly but reflected in discrepancies between different data sets on the same entity such as land use patterns (see e.g. Porwollik et al. 2017). We have not explicitly tested the propagation of input data uncertainty but focused on the uncertainty in the parametrization of our allocation rules. We now include this aspect in the section 2.3 and 4.2 discussing input dataset uncertainties, as suggested.	Sections 2.3 and 4.2
All this should be more explicitly acknowledged in your discussion, so that users are fully aware of the limitations of the dataset. This is my main criticism which I would like to see addressed.	We added text on uncertainty of our rule based approach, the used input and the output data.	Sections 2.2 and 4.2
Figure 2: In general, the figures/maps are nice and the choice of colour palette is adequate, except for figure 2, which uses the "rainbow" colour scheme. The 'rainbow' palette is the default one in many mapping software, and has been widely used in the past. However, it not only poses problem for colour-blind readers (approx. 10% of male population), but also gives misleading perceptions of thresholds in data (e.g. Light and Bartlein, 2004; Hawkins et al., 2015). There is growing support within the scientific community to abandon the use of rainbow colour scheme. It is of course ultimately a	We agree to your suggestion and improved Fig. 2 in the manuscript by dropping the rainbow but applying the viridis-color scheme with a break per color step. We additionally included a further break point resulting in an increased shaded pattern in the probability map (in what has been shaded all red only, now is appearing in yellow to light greenish colors). These finer scaling shows more clearly that a lot of high probability values end up in between 0.9 and 1 but especially a lot between 0.999 and 1.	Figure 2

personal choice from the authors, but I would suggest you redo the map choosing a different colour scheme.		
Page 6, line 222: remove "have been"	We agree and did so.	
Page 13, line 410: remove "of"	We agree and did so.	
Page 18, line 508: remove "in" in "may persist low in"	We agree and did so.	
Referee #4		
I have read the manuscript with much interest to understand the importance of the work and if it really fills a gap in our knowledge. Reading the manuscript has not been much easy because it is too complex because of both the way of presenting the topic and the proposed methods. Soil tillage is an important research issue for its effects on soil conservation and carbon sequestration but the described approach at global scale is not much suitable to help in quantitative assessment of biophysical and bio-geochemical impacts of land use and soil management as claimed by Authors. **They have pointed out clearly the many factors and properties, which can determine the type of soil tillage. Among these are included soil type and depth, climate, crops, rainfed and irrigated crops, socio-economic factors determining the mechanization level of agriculture, etc. Consequently, it results extremely complex and difficult to model all factors and properties.**	Indeed, the decisions made by farmers on which type of tillage to use are complex, substantially more complex than reflected by our rules. We will revise the structure and text of the article where suitable to improve the readability of the article. We do think that providing an explicit data set on tillage types is helpful in the quantitative assessment of biophysical and biogeochemical effects of land use and soil management, as the alternative is to use implicit model assumptions.	Entire manuscript
Particularly, the Authors have used data much	Until now we refrained from describing too many	Section 2.3

different that have required to be resampled and aggregated (Line 220) but no detail has been provided on how that has been made.	technical details concerning the coding as we thought that would blow up and complicate the text even more. For us it was more important to explain the general concept. Indeed, substantial harmonization steps of data formats were necessary to process the different data sources. We have now expanded the description of the harmonization procedure in section 2.3. Full detail on the data processing steps is also provided through the accompanying published source code (Porwollik et al., 2019).	
Many rules have been used for mapping and downscaling but it is not much clear how the Authors have statistically validate them.	We derived rules from qualitative statements found in relevant literature (for CA – erosion, CA- aridity, and CA- crop type, the threshold of 2 ha per ha to distinguish between small and large scale farming). For downscaling CA rather to large than to small field size we approved of the relation between CA area and farm size found via a statistical assessment shown in Figure S3 with the coefficient of determination r^2=0.66. Further prove of statistical relations among mapping variables definitely are an interesting challenge to be explored but are momentary outside the scope of this mapping exercise. In order to capture the uncertainty of the logit model we included the sensitivity test with different variable combinations and functional parameters. In the manuscript, section 4.2 we add text discussing more explicitly which rules are based on qualitative or statistical relations found in the literature.	Section 4.2
The manuscript should be organized better to allow readers to follow the development of the objectives in materials, methods, and results. The	We revised the entire manuscript for better streamlining the narrative.	Entire manuscript

quality of writing should be checked and improved.		
There is an excessive use of first person: we	There are different perspectives on the use of active and passive voice in articles. We find that active voice makes articles substantially easier to read,. We reduced the occurrence of ‘we’ or ‘our’-formulations’ in the entire manuscript.	Entire manuscript
The title should be made more effective and to reflect better the objectives.	We agree and improved the title of the manuscript.	Generating a rule-based global gridded tillage dataset
The abstract should summarize better the whole manuscript. **The Introduction section should be made more fluent and readable.** **The novelty should be explained better and the objectives made clearer.** **Methods should be organized better to allow readers understanding how methods have been used.** **Results and Discussion sections would require to be supported by improved Methods and data section.**	We improved the manuscript in terms of structural adjustments and better separation into sections. Further we improved the abstract, introduction, formulation of objectives, data and method, and the discussion section in the course of this review process as suggested by all referees.	Entire manuscript
Referee #5		
The presentation is almost clear, but the English can be improved.	We carefully checked the language and improved the wording and formulations.	Entire manuscript
Line 58: What is HYDE?	HYDE stands for ‘History Database of the Global Environment’. HYDE is an internally consistent combination of historical population estimates and allocation algorithms with time-dependent weighting maps for land use including grassland but also cropland including its irrigated and rainfed shares. We now explain that abbreviation and have corrected the reference.	Prestele et al. (2018) mapped reported national values of CA area from Kassam et al. (2015) to cropland of the History Database of the Global Environment database (HYDE; Klein Goldewijk et al. (2017)) for the year 2012.

Line 60: "For downscaling national values Prestele et al. (2018)…" this sentence is too complicated. Should be rephrased.	We agree and rephrased the sentence.	Based on literature findings, Prestele et al. (2018) developed a CA adoption index per grid cell composed by a set of spatial predictors as aridity, field size, soil erosion, market access, and poverty for downscaling reported national CA area values. Their global map of CA at a spatial grid resolution of 5 arc-minutes is freely available for application in impact assessments in global model simulations.
Line 94: What is ESM?	Thank you for that hint – we have simply overseen to define this abbreviation. At first occurrence of the word 'Earth system model' in our manuscript we now introduced the abbreviation 'ESM'.	Section 1
Line 106: I do not understand the sentence "… or can assess different tillage impacts just in form of scenarios". Should be rephrased.	We agree and rephrased the section.	In the absence of detailed area and tillage type information, the global ecosystem modeling community currently can assess difference of contrasting tillage type impacts just in form of stylized scenarios simulating the effect on the entire cropland area (Del Grosso et al., 2009; Olin et al., 2015; Pugh et al., 2015). One recent exception is the assessment by Hirsch et al. (2018) who assess the effects of an altered albedo from residues used for soil cover on CA areas, using the data of Prestele et al. (2018).
Line 110: "increase understanding of the drivers for different tillage practices". What do the authors mean by "drivers"?	We agree and revised the section.	The objective of this study is to a) increase the understanding of differences in tillage practices at the global scale b) formulate rules to spatially map tillage systems to the grid scale, and c) develop an open source and open data crop-specific tillage system dataset for the parameterization of tillage events and area in global ecosystem models and assessments. In order to do so we develop a global tillage system classification. Further we analyze underlying causes for the occurrence of different tillage systems and make use of available data in order to map them to a global grid of 5 arc-minutes resolution.
Line 222: "We developed several mapping rules have been in order to allocate the…"this sentence is too complicated. Should be rephrased.	We agree and improved the sentence.	We developed several mapping rules to allocate the six tillage system to the grid scale, employing a decision tree as shown in Fig. 1.
Line 228: Here the authors mentioned the depth of 15 cm, but claimed that "we decided for a minimum depth of mechanized tillage of 20 cm" above. Please explain this inconsistency (the same for Figure 2).	We improved figure 1 and the entire calculation for the fraction of rotational tillage crops on soil deeper than 15 but shallower than 20 cm depth to bedrock because of this detected inconsistency. That cropland fraction is now	We applied a downscale algorithm of national reported CA area values on potential CA area (see Fig. 1 box "Downscaling"; see following section for more details). The remaining cropland not being assigned to CA is checked again for soil depth to bedrock. In case it was lower than 20 cm, the cropland was assigned to reduced tillage assuming less depth, frequency,

	newly allocated to the reduced tillage system. An updated version of the tillage data set and R-script will be provided in the context of this revision process.	mixing efficiency or alternative cultivation practices. In case of soil depth to bedrock of 20 cm or more the remaining cropland was depending on crop type either mapped to the conventional annual or rotational tillage system following the finding of Kouwenhoven et al. (2002) mentioned above for perennial weed management.
Line 533: "global ecosystem models currently run on 0.5° resolution and may have to aggregate the data for input usage" this is not always the case. In many ecosystem models (e.g. ORCHIDEE), their dynamics are simulated at a coarse resolution, but they divide the large model pixel to smaller ones in considering the agricultural processes.	Thank you for the hint. We see that the sentence was generalizing current spatial resolution in global model simulations too much so we rephrased it also to hint at the uncertainty regarding aggregation.	The resolution of the generated dataset with 5 arc-minutes is quite high. Global ecosystem models are currently mostly run at a coarser resolution than our dataset's resolution and the tillage data may have to be aggregated in such cases. This could introduce further uncertainty to the area under a certain tillage system.
Referee #6		
This paper does not adhere to a single unit to describe area. The abstract and discussion use "Mkmˆ2" while all figures and tables use "ha". Readers cannot compare the different units directly and need to convert "ha" to "Mkmˆ2". Thus, I recommend that the authors use "kmˆ2" instead of "ha" in all the figures and tables. The main document should be also modified accordingly.	We agree and harmonized all area unit indication in the text and figures of the entire manuscript to km².	Entire manuscript
I tried to run R script on my PC; however it did not run because it required some data to run in my environment. Thus, I recommend that sample R script should be provided with sample input dataset and output dataset. Then reader can run R script with the data provided and verify their output against a sample output dataset that can be involved. Otherwise, the reader cannot check whether their results were correctly reproduced or not.	It is correct that in order to run the script the user needs to download the input data sets as indicated in our article, R-code but also described in the meta-data at the repository's websites. We now include sample input and output data which can be applied for testing the functionality of the R-script, when setting 'sample_calc' to 'TRUE' in the beginning of the script.	R-code V.1.1
In terms of figure 1, I	Thank you for this	R-code V.1.1

suppose that each box in the figure should correspond to the R script. Thus, it is better to add information (ex. line number) that indicates which part of the R script corresponds to the boxes, and also to show the location in the Rscript, where different crop-specific tillage systems are evaluated. According to these, readers can easily understand the R script, which is also the authors' objective.	suggestion. We have now harmonized the wording of the tillage systems between the manuscript, the data-flow diagram (Figure 1) and the accompanying R-script. We improved the structure of the R-script to be more in line with the steps described in the manuscript and Fig 1. In the R-script we also added comments, indicating which section generates which table and values of the manuscript.	
Own considerations:		
	Improved Fig. S5, Replaced 12th panel scatterplot with correct output for fields +100% slope increase instead of erosion +100%	Supplement (SI)
	Recalculated crop mix and field size interpolation which lead to (small) changes in the entire results so we redid all tables, figures in manuscript and in the online versions of the R-code and data	Entire manuscript, Supplement (SI), R-code V.1.1, and tillage dataset V.1.1
	Improved calculation for reduced and rotational tillage	Entire manuscript, Supplement (SI), R-code V.1.1, and tillage dataset V.1.1

Generating a rule-based global gridded tillage ~~-~~dataset

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Abstract. Tillage is a central element in agricultural soil management and has direct and indirect effects on processes in the biosphere. Effects of agricultural soil management can be assessed by soil, crop, and ecosystem models but global assessments are hampered by lack of information on the type of tillage ~~type~~ and their spatial distribution. This study describes the generation of a ~~global~~ classification of tillage practices and presents the spatially explicit mapping of these crop-specific tillage systems for around the year 2005.
Tillage practices differ by the kind of equipment used, soil surface and depth affected, timing, and their purpose within the cropping systems. ~~-~~We ~~-~~classified the broad variety of globally relevant tillage practices to ~~into~~ six ~~tillage systems~~categories: ~~.-~~no-tillage in the context of Conservation Agriculture, traditional annual, traditional rotational, rotational, reduced, and conventional annual tillage. The identified tillage systems were allocated to gridded crop-specific cropland areas with a resolution of 5 arc-minutes. ~~The a~~Allocation rules were based on literature findings and combine area information on crop type, water management regime, field size, water erosion, income, and aridity. We ~~allocated~~ scaled reported national Conservation Agriculture areas down to grid cells via a probability-based ~~downscaling~~ approach for 54 ~~reporting~~ countries.~~-~~ We provide area estimates of the six tillage systems aggregated to global and country scale. We found that 8.67 Mkm² of global cropland area were tilled intensively at least once a year whereas the remaining 2.65 Mkm² were tilled less intense. Further we identified 4.67 Mkm² of cropland as area where Conservation Agriculture could be expanded to under current conditions. ~~The dynamic definition of the allocation rules and accounting for national statistics, such as the share of Conservation Agriculture per country, also allows for deriving datasets for future global soil management scenarios. We present the mapping of six tillage systems: no-tillage in the context of Conservation Agriculture (1.1 Mkm²), traditional annual (4.01 Mkm²), traditional rotational (0.65 Mkm²), rotational (0.74 Mkm²), reduced (0.15 Mkm²), and conventional annual tillage (4.65 Mkm²). Further we identified a total area of 4.67 Mkm² ha as potentially suitable area for Conservation Agriculture under assessed current conditions. We elaborate on the results of a sensitivity analysis for our downscale approach as well compare tillage system area results to literature estimates.~~

The tillage classification enables the parameterization of different soil management practices in various kinds of model simulations. The crop-specific tillage dataset indicates the spatial distribution of soil management practices, which is prerequisite to assess erosion, carbon sequestration potential, as well as water, and nutrient dynamics of cropland soils. The dynamic definition of the allocation rules and accounting for national statistics, such as the share of Conservation Agriculture per country, also allows for deriving datasets for historical and future global soil management scenarios. The resulting ~~presented~~ tillage~~-~~ system dataset and source code are accessible via an open-data repository ~~for modeling communities interested in the quantitative assessment of biophysical and biogeochemical impacts of land use and soil management~~ (DOIs: 10.5880/PIK.2019.009 ~~10.5880/PIK.2018.012~~ and 10.5880/PIK.2019.010 (Porwollik et al., 2019a, b)~~10.5880/PIK.2018.013~~).

1 Introduction to tillage

Global cropland covers an area of about 15 Mkm^2 (Ramankutty et al., 2008), which is approximately 13% of global ice-free land. C~~, whereas c~~ropland and associated land management contribute~~s~~ about 4.5% of global anthropogenic GHG emissions accounting for emissions from rice cultivation, peatland drainage, and ~~N~~ nitrogen fertilizer application in the year 2000 (Carlson et al., 2016). Tillage and plowing (further jointly referred to as tillage) are practiced on most of this cropland (Erb et al., 2016; Pugh et al., 2015). Tillage comprises farm operations usually practiced for seedbed preparation, weed and pest control, or incorporation of soil amendments. According to Schmitz et al. (2015) conventional tillage can be distinguished on the one hand into traditional systems with manual labor and tools, and on the other hand mechanized systems. Conventional tillage usually comprises inversion and mixing of the soil layers with the biophysical ~~of~~ loosening of the soil, leading to altered temperature and soil moisture levels in the affected soil layer (S1 for further terms and definitions used in this study). Current global soil management practices trend towards a reduction of tillage operations and intensity (Derpsch, 2008; Smith et al., 2008). Reduced intensity of the tillage operation as either in the case of strip-, mulch-, ridge- and no-tillage is also referred to as conservation tillage (CTIC, 2018). Reduced tillage practices are especially suitable for agricultural production (a) of grain crops such as cereals, legumes, and oilseed crops (Giller et al., 2015); (b) on large, mechanized farms to save labor (Mitchell et al., 2012; Ngwira et al., 2012), fuel (Young and Schillinger, 2012), and machine wearing (Saharawat et al., 2010); (c) under arid climate conditions, because of its soil moisture preserving effect (Kassam et al., 2009; Pittelkow et al., 2015); and (d) on soils with high erosion rates (Govaerts et al., 2009; Schmitz et al., 2015).

Up to now there has been only little effort in the classification and area assessment of tillage systems at the global scale. Erb et al. (2016) reviewed data availability of land management practices at the global scale and found that there was no continental or global dataset on area, distribution, and intensity of tillage practices. They report 7.43 Mkm² ~~of cropland~~ to be under high intensity tillage comprising the cropland area of annual crops ~~comprisingto be~~ ~~annually harvested area to be under high intensity tillage~~ and 4.73 Mkm² of area under low intensity tillage, which comprises the cropland area of perennial crops, zero-tillage as stated by Derpsch et al. (2010), and young and temporal fallow cropland area as reported by Siebert et al. (2010).

The only global statistical data on a kind of tillage system area is provided by the FAO for the extent of Conservation Agriculture (CA) area (FAO, 2016) at the national scale. CA is a~~, which~~ soil management concept ~~includ~~comprising~~es~~ minimum soil disturbance (through direct seeding techniques), a permanent organic soil cover as mulch or green manure, and a diversified crop rotation (Kassam et al., 2009). It is ~~practiced~~ applied on ~~CA covers~~ about 10% of the global cropland area (FAO, 2016). ~~The top-three adopting countries of CA in terms of area are Argentina, Paraguay, and Uruguay (73.51%, 66.67%, 46.13% of their arable land respectively) (FAO, 2016).~~ Widest area spread of CA practice is reported for South America followed by North America (accounting for over 84.6 % of total global CA area), where it has been originally developed. Adoption of CA is much lower in Europe, Asia, Australia & New Zealand, and with lowest adoption rate in Africa (1.1%, 2.3%, 11.5%, and 0.3% of reported total global CA area respectively) (Derpsch et al., 2010). The top-three adopting countries of CA in terms of area are Argentina, Paraguay, and Uruguay (73.51%, 66.67%, and 46.13% of their arable land respectively) (FAO, 2016).

Prestele et al. (2018) mapped reported national values of CA area ~~reported by~~ from Kassam et al. (2015) to ~~HYDE~~ cropland of the History Database of the Global Environment database (HYDE;~~ (HYDE:~~ Klein Goldewijk et al. (2017)) for the year 2012~~(Klein Goldewijk et al., 2017)~~. ~~For downscaling national values Prestele et al.~~

~~(2018) developed a CA adoption index per grid cell composed by a set of spatial predictors as aridity, field size, soil erosion, market access, and poverty, based on literature findings resulting in a map at a spatial grid resolution of 5 arc-minutes available to interested users.~~ Based on literature findings, Prestele et al. (2018) developed a CA adoption index per grid cell composed by a set of spatial predictors as aridity, field size, soil erosion, market access, and poverty for downscaling reported national CA area values. Their resulting global map of CA area at a spatial grid resolution of 5 arc-minutes can be applied for impact assessments in global model simulations.

Data on tillage practices are available, e.g. for the USA through the reporting of the National Crop Residue Management Survey published by Conservation Technology Information Center (http://www.ctic.purdue.edu/CRM/crm_search/, accessed 08/21/2018). The survey was pursued at national level until 2004 and continued for a subset of counties for subsequent years reporting on farming area managed under conventional, reduced, and conservation tillage (with further ~~their~~ sub-categories of no-, ridge-, and mulch-tillage). For Europe, tillage practices have most recently been assessed by the Survey on agricultural production methods (SAPM) in 2010 based on census and sample survey data and published by EUROSTAT (http://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Survey_on_agricultural_production_methods_(SAPM), accessed 08/23/2018). In the EUROSTAT data portal farm type and size, and their corresponding area managed under the tillage categories: conventional, conservation tillage, and zero-tillage (often used as a synonym for no-tillage as referring to direct seeding techniques) are reported. Analyzing tillage practices in the EU-27 for the year 2010, it has been found that on average the share of conservation and zero-tillage practices increases with the size of the arable land area of a farm holding (EUROSTAT, 2018).

~~Erb et al. (2016) reviewed data availability of land management practices at the global scale and found that there was no continental or global dataset on area, distribution, and intensity of tillage practices. They report 7.43 Mkm^2 of cropland comprising annually harvested area to be under high intensity tillage and 4.73 Mkm^2 of area under low intensity tillage, which comprises the cropland area of perennial crops, zero-tillage as stated by Derpsch et al. (2010), and young and temporal fallow cropland area as reported by Siebert et al. (2010).~~

Soil, crop, vegetation, erosion, and Earth system models (ESMs) (in the following jointly referred to as ecosystem models) can be applied to assess the effect of different tillage practices on ecosystem elements, fluxes and stocks. Some global carbon studies assess the climate mitigation potential of soils managed with no-tillage compared to conventional tillage, which was simulated as a temporally limited enhancement of the decomposition factor on the soil carbon pools under cultivated cropland (Levis et al., 2014; Olin et al., 2015; Pugh et al., 2015; Smith et al., 2008). More process-based representations of the tillage effect are applied in models as the decision support system for agrotechnology transfer ~~CSM for DSSAT-~~- cropping system model (DSSAT-CSM, White et al. (2010)), and the crop growth simulator (CROPGRO-soybean, Andales et al. (2000) having direct and indirect biophysical effects on soil, water, crop yield, and emissions. Another field of global scale studies assessing the tillage effect refers to the analysis of albedo enhancement perceived in cases of no-tillage in conjunction with associated increased residue levels left on the soil surface ~~of the field~~ (Hirsch et al., 2017; Lobell et al., 2006). Furthermore, tillage is important in soil erosion assessment studies, often represented within the context of the land management factor amplifying sub-factors as surface cover and ~~surface~~ roughness (Nyakatawa et al., 2007; Panagos et al., 2015).

McDermid et al. (2017) reviewed regional ~~models~~ and ESMs' approaches of representing agricultural management practices and land use conversion with a focus on climate and land surface interactions, including tillage modifying carbon stocks in the soil as well as biogeophysical surface attributes. They reveal sources of uncertainty due to missing land management data and limited representation of processes in current assessment models. In regard to the tillage ~~implementation~~ effect ~~in ESMs,~~ they elaborate on the findings of Levis et al. (2014) who found decreased soil carbon levels ~~under~~ below cropped and cultivated land compared to land without cultivation. McDermid et al. (2017) ~~state~~ mention a potential overestimation of the efficacy of no-tillage practices' contributions to mitigate anthropogenic carbon by enhanced carbon stock based on findings of Powlson et al. (2014).

Pongratz et al. (2017) also reviewed data availability and process implementations within ESMs for ten land management practices and resumed tillage to be currently underrepresented. They recommend simple and complex methods to model tillage effects on albedo, soil moisture, respiration, and resulting ~~effects~~ impact on soil carbon stocks and fluxes. In the absence of detailed tillage area and type information, the global ecosystem modeling community currently can assess difference of contrasting tillage type impacts just in form of stylized scenarios, simulating the effect on the entire cropland area ~~The ecosystem modeling community relies on sometimes nontransparent assumptions on type and spatial distribution of tillage systems, or can assess different tillage impacts just in form of scenarios~~ (Del Grosso et al., 2009; Olin et al., 2015; Pugh et al., 2015). One recent exception is the assessment by Hirsch et al. (2018) who ~~assess~~estimate the effects of an altered albedo from residues used for soil cover on CA areas, using the spatial data of Prestele et al. (2018).

The objective of this study is to a) increase the understanding of differences in ~~the drivers for different~~ tillage practices ~~and their spatial distribution~~ at the global scale b) formulate rules to spatially map tillage systems to the grid scale, and c) develop an open source and open data crop-specific tillage system dataset for the parameterization of tillage events and area in global ecosystem models and assessments. In order to do so ~~For this~~ we develop a global tillage system classification. Further we ~~aim to formulate a set of rules by~~ analyz~~e~~ing underlying causes ~~and drivers~~ for the occurrence of different tillage systems and make use of available data in order to map them to a global grid of 5 arc-minutes resolution.

2 Data and method

2.1 ~~Figure 1~~Tillage system classification

Globally tillage systems differ by the kind of implement used, soil depth and share of soil surface affected, mixing efficiency, timing, frequency, and by their purpose within the relevant cropping systems (Table 1).

Conventional tillage, often done with a moldboard plow refers to the inversion and mixing of soil layers for seedbed preparation, incorporation of soil amendments, weed, pest, and residue management~~, and incorporation of soil amendments~~. In traditional tillage systems soils are usually managed with hand tools, e.g. hoe or cutlass (Schmitz et al., 2015), which is very labor and time intensive. The application of animal-drawn plows or the use of a moldboard plow attached to some motorized vehicle result in increased soil depth and mixing efficiencies~~y~~

of the tillage operation compared to traditional tillage implements. In the case of ~~For~~ CA, ~~we assume~~there is only ~~the~~ a minimal mechanical soil disturbance by direct seeding equipment or none in the case of broadcasting seeds. The soil depth affected by the tillage operation is determined by the soil depth to bedrock, the implement used to till the soil, and by the purpose of the tillage event. A moldboard plow usually inverts and mixes the soil layers up to 20-30 cm depth. Pimental and Sparks (2000) state the minimum soil depth for agricultural production to be 15 cm. Whereas Kouwenhoven et al. (2002) ~~state~~find that for burying green manure and annual weed, a minimum tillage depth of 12 cm to be necessary, and suggest 20 cm for the management of perennial weeds. We decided for a minimum depth of mechanized tillage of 20 cm. For traditional tillage with manual labor, tillage is assumed to reach only to a lesser depth, because of limited capacity to penetrate the soil profile (Schmitz et al., 2015). The affected depth by minimum soil disturbance practices under CA is assumed to be as deep as the seed placement requires, which is stated as approximately 5 cm by White et al. (2010) for no-tillage systems.

In conventional tillage systems, the tillage implement is usually applied on the entire soil surface to be effective. In contrast to that, no-tillage under CA ~~maximal~~ may affect at most 20 to 25% of the soil surface during the direct seeding procedure (Kassam et al., 2009; White et al., 2010). On the field, reduced tillage as partial disturbance of the soil surface in case of strip-, mulch- or ridge tillage can be achieved by applying either an inverting implement to a lesser soil depth or a lower share of soil surface affected, by using harrows or disks, or by less field passes. Reduced tillage practice can be simulated in the form of~~as with~~ lower soil disturbance, frequency, depth, mixing efficiency, or higher residue share left on the soil surface ranging between values of conventional and no-tillage (15 to 30%).

Tillage mechanically loosens the soil by decreasing the bulk density of the soil. Soil bulk density and pore space determine the levels of surface contact between seeds and soil particles, root growth, and water infiltration. The mixing efficiency of tillage describes the degree of homogeneity achieved e.g. when burying crop residues and redistributing soil particles in the affected soil horizon. The type of soil, its moisture content, and the speed of the tillage practice are further determining factors for the mixing efficiency of tillage (White et al., 2010) under field conditions. Too intensively or inappropriately tilled soils over a longer time period exhibit the destruction of soil aggregates by increasing bulk density leading to compaction or crusting (White et al., 2010). The mixing efficiency can be modelled as a factor modifying the homogeneity level of soil components and associated characteristics.

Conventional tillage both in mechanized and traditional farming systems leaves a low portion of residues covering the soil surface after seeding - usually less than 15% (CTIC, 2018; White et al., 2010). Reduced tillage may leave 15-30% whereas in CA systems minimum soil surface covered by organic mulch is defined as at least 30% after the seeding operation (CTIC, 2018).

~~We set~~ T~~t~~iming and frequency of soil disturbance by tillage depend~~ing~~ on the type of cropping system. For annual crops, tillage is performed annually at the time of establishment, ~~or~~ after harvest, or both. When modelling perennial crops, the interval of the main tillage events on fields should reflect the length of the ~~entire~~ perceived entire plantation cycle. During the ~~year~~ growing period ~~for annual and perennial cropland~~ less intense tillage may be necessary for weed management or intended inter-cropping purposes several times. This soil management is locally restricted to the space between the rows of the main crop and ~~could~~ can be replaced by herbicide applications. Within CA managed systems disturbance of the soil occurs only at the time of seeding. Weed in CA systems is either managed by sustaining a permanent soil cover of either mulch or cover crops, by diversified rotations, ~~and~~ or by application of herbicide so that no further mechanical soil disturbance is necessary during the growing season.

~~The soil depth affected by the tillage operation is determined by the soil depth to bedrock, the implement used to till the soil, and by the purpose of the tillage event. A moldboard plow usually inverts and mixes the soil layers up to 20-30 cm depth. Pimental and Sparks (2000) state the minimum soil depth for agricultural production to be 15 cm. Whereas Kouwenhoven et al. (2002) state that for burying green manure and annual weed, a minimum tillage depth of 12 cm to be necessary, and suggest 20 cm for the management of perennial weeds. We decided for a minimum depth of mechanized tillage of 20 cm. For traditional tillage with manual labor, tillage is assumed to reach only to a lesser depth, because of limited capacity to penetrate the soil profile (Schmitz et al., 2015). The affected depth by minimum soil disturbance practices under CA is assumed to be as deep as the seed placement requires, which is stated as approximately 5 cm by White et al. (2010) for no-tillage systems.~~

~~Conventional tillage both in mechanized and traditional farming systems leaves a low portion of residues covering the soil surface after seeding - usually less than 15% (CTIC, 2018; White et al., 2010). Reduced tillage may leave 15-30% whereas in CA systems minimum soil surface covered by organic mulch is defined as at least 30% after planting (CTIC, 2018).~~

~~Tillage mechanically loosens the soil by decreasing the bulk density. The mixing efficiency of tillage describes the degree of homogeneity achieved when burying crop residues and redistributing soil particles in the affected soil horizon. Soil bulk density and pore space determine the levels of surface contact between seeds and soil particles, root growth, and water infiltration. Soil characteristics as moisture, temperature, are altered by the mixing effect of tillage. The type of soil, its moisture content, and the speed of the tillage practice are further determining factors for the mixing efficiency of tillage (White et al., 2010) under field conditions. Too intensively or inappropriately tilled soils over a longer time period exhibit the destruction of soil aggregates by increasing bulk density leading to compaction or crusting (White et al., 2010). The mixing efficiency can be modelled as a factor modifying the homogeneity level of soil components and associated characteristics.~~

~~In mechanized conventional and traditional tillage systems, the implement is usually applied on the entire soil surface to be effective. In contrast to that, no-tillage under CA maximal may affect 20-25% of the soil surface during the direct seeding procedure (Kassam et al., 2009; White et al., 2010). On the field reduced tillage as partial disturbance of the soil surface in case of strip-, mulch- or ridge tillage can be achieved by applying either an inverting implement to a lesser soil depth or lower share of soil surface affected, by using less soil disturbing harrows or disks, or by less field passes. Reduced tillage practice could be simulated as with lower soil disturbance frequency, depth, mixing efficiency, or higher residue share left on the soil surface ranging between values of conventional and no-tillage.~~

Based on the literature findings mentioned above we consider six different tillage systems, namely no-tillage in the context of Conservation Agriculture, conventional annual, rotational, traditional annual, traditional rotational, and reduced tillage (Table 1).

(Table 1)

2.2 Datasets used for mapping tillage systems to the grid

For mapping the six tillage systems, spatial indicators on the basis of several environmental and socio-economic datasets are applied (Table 2). The basic data layer to this mapping study is the cropland dataset by the spatial production allocation model further referred to as SPAM2005 by the International Food Policy Research

Institute and International Institute for Applied Systems Analysis (IFPRI/IIASA, 2017b). It reports physical cropland area for 42 crop types (Table S2 for a list of crop types)~~,~~ for the year 2005. ~~The spatial resolution of the dataset is 5 arc-minutes.~~ SPAM2005 is a result of a disaggregation of national and sub-national data sources in an cross-entropy approach. The SPAM2005 dataset comprises four technology levels of crop production, distinguishing high input irrigated from purely rainfed ~~areas~~ with further distinction of rainfed ~~areas~~ into high input, low input, and subsistence production per crop type and grid cell (You et al., 2014). In this study only the entire physical cropland and the separated irrigated and rainfed cropland were used per grid cell. Adding up the reported cropland area of SPAM2005 for 42 crop types results in a total sum of 11.31 Mkm^2.

The ~~cropland by IFPRI/IIASA (2017b) comes along with a~~ grid cell allocation key to country accompanying the SPAM2005 cropland dataset ~~-~~(IFPRI/IIASA, 2017a)~~, which~~ was ~~has been used~~ applied in this study for any grid cell aggregation to country scale.

Sub-national aggregations of grid cells to state or province level were done with the Global Administrative Areas data base (Global Administrative Areas, 2015).

The dataset on soil depth to bedrock (Hengl et al., 2014) has been retrieved from SoilGrids, which is a soil information system reporting spatial predictors of soil classes and soil properties at several depths. It has been derived on the basis of the United States Department of Agriculture (USDA) soil taxonomy classes, World Reference Base soil groups, regional and national compilations of soil profiles, several remote sensing, and land cover products using multiple linear regressions. The dataset reports on the absolute depth to bedrock (cm) per grid cell ~~at 5 arc-minutes resolution~~.

The global gridded field size dataset by Fritz et al. (2015) has been derived and validated on the basic of a crowd-sourcing campaign. It reports four field size classes as “very small” (smaller than 0.5 ha), “small” (0.5 to 2 ha), “medium” (2 to 100 ha), and “large” (larger than 100 ha) (Herrero et al., 2017) for the year 2005 ~~at 0.5 arc-minutes resolution~~. The field size and the SPAM2006 datasets both use the cropland extent presented in Fritz et al. (2015).

The Global Land Degradation Information System (GLADIS) (Nachtergaele et al., 2011) reports land degradation types and their spatial extent around the year 2000. From this database the global gridded water erosion data has been selected. The water erosion data reports the sediment erosion load (t ha^{-1} year^{-1}) per ~~5 arc-minutes~~ grid cell which the authors derived by applying the Wischmeier equation (Wischmeier and Smith, 1978). Values of the data range from 0 to 12,110 t ha^{-1} year^{-1} with highest water erosion levels occurring in mountainous areas.

The aridity index dataset was retrieved from the Food and Agriculture Organization Statistics (FAO, 2015). The aridity index was calculated as the average yearly precipitation divided by the average yearly potential evapotranspiration (PET), based on Climate Research Unit (CRU) CL 2.0 climate data averaged for the years from 1961 to 1990 applying the Penman-Monteith method. ~~The aridity index dataset has a 10 arc-minutes resolution.~~ It reports values per grid cell ranging from 0 to 10.48, where values smaller than 0.05 are regarded as “hyper arid”, 0.05-0.2 as "arid”, 0.2-0.5 as “semi-arid”, 0.5-0.65 as “dry humid”, and values larger 0.65 as “humid”.

(Table 2)

The online data base AQUASTAT reports annually the spread of Conservation Agriculture (CA) practices at the national scale (FAO, 2016). From this data source, national CA area values were retrieved for all 54 countries that reported any CA with the total area sum of 1.1 Mkm². Not all of these countries reported values for the year 2005, so that values closest to 2005 were selected from the available set, giving preference to data availability over matching the year 2005.

The average farm size per country dataset (n=133) (Lowder et al., 2014) is based on FAO farm size time series data. National average farm size was largest in land-rich countries, with the top-three countries being Australia (3243.2 ha), Argentina (582.4 ha), and Uruguay (287.4 ha) (Lowder et al., 2014). The authors found average farm size to increase with elevated income level of a country.

Further we retrieved the income level per country by World Bank (2017) for the year 2005. The data refers to four categories of countries gross national income (GNI capita^{-1} year^{-1}), as “Low income” (less than 875 US $), “Lower middle income” (876-3,465 US $), “Upper middle income” (3,466-10,725 US $), and “High income” (more than 10,725 US $).

2.3 Processing of input data and mapping rules

For calculation purposes, all gridded input datasets mentioned above were harmonized in terms of spatial extent, resolution, and origin. The spatial extent of the target dataset comprises all cropland cells reported by SPAM2005 (IFPRI/IIASA, 2017b). Targeted resolution is 5 arc-minutes, which partially required resampling and (dis-)aggregation of the applied datasets using the R (R Development Core Team, 2013) version 3.3.2 loading packages ‘raster’ (Hijmans and van Etten, 2012), ‘fields’ (Nychka et al., 2016), and ‘ncdf4’ (Pierce, 2015). More details on the input data harmonization and processing can be found in the ~~(also see~~ accompanying R-code (Porwollik et al., 2019a)~~)~~.

We developed several mapping rules ~~have been in order~~ to allocate the six ~~derived~~ tillage systems ~~mentioned above~~ to the grid~~-~~ cell scale, employing a decision tree as shown in Fig. 1. The decision tree approach has also been applied in other spatial mapping exercises, e.g. in Verburg et al. (2002) and Waha et al. (2012). Hierarchical classification procedures based on expert-rules can be used to distribute data of a larger spatial (e.g. administrative) unit~~s~~ to the grid cell level (Dixon et al., 2001; Siebert et al., 2015; van Asselen and Verburg, 2012; van de Steeg, 2010).

As a first step, the SPAM2005 cropland dataset is masked for grid cells reporting cropland but soil depth to bedrock of less than the required 15 cm for agricultural production according to Pimental and Sparks (2000) (Fig. 1).~~.~~ This contextual mismatch between these two datasets ~~might~~may be caused by different input data used by the producers or by their method of averaging values within one grid cell, ~~where~~ in which the soil depth to bedrock is heterogeneous~~in reality would be a more heterogeneous soil depth to bedrock setting~~. The entire cropland of these shallower grid cells is allocated directly to the reduced tillage system area, where ~~tillage practices as~~ ridging or raised beds may be practiced by the farmer, ~~because~~ because of physical hindrance for inverting tillage practices at increased depth.

The remaining cropland is treated separately~~d~~ for~~into~~ annual and perennial ~~cropland~~ crops following Erb et al. (2016)’s findings, differing between plant type associated tillage by intensity in terms of frequency and timing of the tillage operation (Table S2 for crop type classification).

As a further step, we distinguished tillage practices per water management regime. We assumed that soils of irrigated crops are more regularly exposed to some level of mechanical soil surface alteration, i.e. leveling off of the surface in order to distribute irrigation water most efficient and homogeneous over the field. We allocated all irrigated annual cropland either to traditional or conventional annual tillage area depending on field size and income level (Fig. 1).

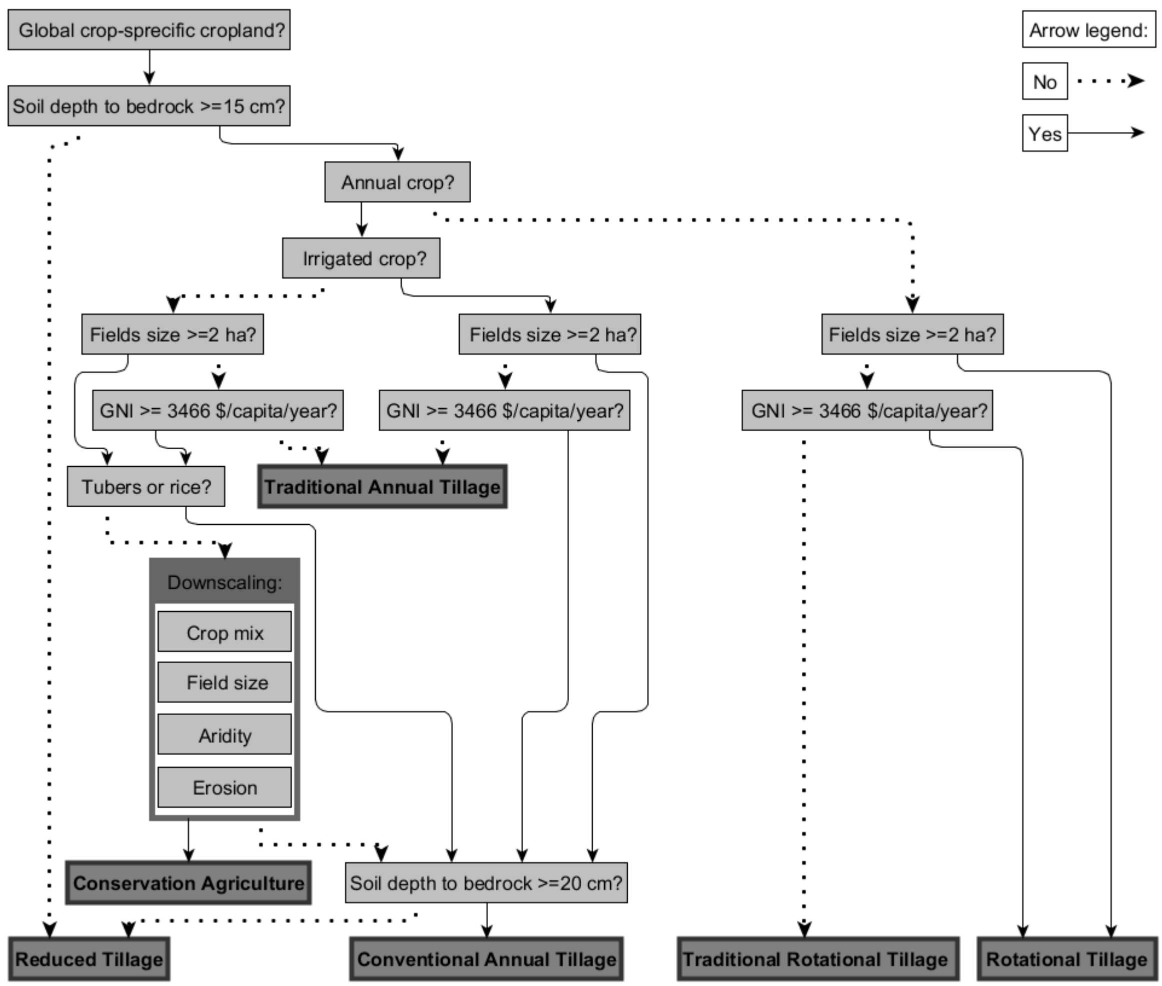
Annual and perennial tillage systems, both are further distinguished by the level of mechanization and commercial orientation of the crop production. ~~unit.~~ We follow the definition for smallholder farming used in Lowder et al. (2016) ~~for smallholder farming~~, if cultivation area is smaller than 2 ha. A~~a~~ccording to Fritz et al. (2015), field size can be regarded as a proxy for agricultural mechanization and human development. Further Levin (2006) found that field size and farm size are positively related. ~~and according to Fritz et al. (2015), field size can be regarded as a proxy for agricultural mechanization and human development.~~ Based on these findings, we apply the field size dataset as a proxy for farm size and mechanization. We categorize cropland per grid cell reporting field size equal or larger than 2 ha as 'large' scale assuming~~with~~ access of the farmer to ~~mechanization~~ mechanized farming equipment and field size smaller than 2 ha as 'small' scale farming with rather manual labor. Field size data is not available for all grid cells where SPAM2005 reported cropland. Consequently we interpolated for missing field size grid cell values, using the mean of surrounding grid cell values. The spatial distance to the Hawaiian Islands was too far for this operation, so there field size ~~has been~~was set to value of 2 ha, assuming a land restriction to field size due to the island's geographic pattern and in absence of any alternative information.

We further assume that animal draught power and mechanized soil management practices on a farm also occur as a function of income, indicating the financial capital a farmer might have access to. Therefore, we additionally apply the national average income level dataset to differentiate between small field sizes in higher income countries, where access to financial capital for investment into farm equipment is perceived easier than for farmers with small field sizes in lower income countries. In order to do so, we ~~summarized~~ reclassified countries reported in the income dataset considered "low" and "lower-middle income" as 'low income', and those countries formerly considered "upper middle" and "high income" as 'high income' in this study. In grid cells reporting newly derived small field size and low income, we then allocated perennial cropland to traditional rotational tillage and annual cropland to traditional annual tillage. In high income countries or in a grid cell reporting field size larger than 2 ha situated in low income countries, perennial cropland was assigned to rotational tillage and annuals' cropland to conventional annual tillage assuming a rather commercially oriented farming system with access to market, financial capital, and therefore mechanized soil management equipment (Fig. 1).

~~As a further step, we distinguished arable production per water management regime following the finding of Kassam et al. (2009) who state, that much of the CA development to date has been associated with rainfed arable crops. We assumed that soil of irrigated crops is more regularly exposed to some level of mechanical soil surface alteration by farming practices, because efficient and equal distribution of water requires some leveling off of the field to flatten the surface in order to distribute irrigation water most efficient and homogeneous over the field. We allocated all irrigated annual cropland area either to annual traditional or conventional tillage area depending on field size and income level (Fig. 1).~~

~~Cropland areas of 22 annually planted rainfed crop types were considered as suitable for CA practice~~~~following the finding of Kassam et al. (2009) who state, that much of the CA development to date has been associated with rainfed arable crops.~~. ~~All annual rainfed tubers or rice croplands are excluded from the CA-suitable area following Pittelkow et al. (2015), who reported larger yield penalties for these crop types when applying no-tillage practices. Rice is often produced as paddy rice, requiring puddling, which is a practice modifying the soil~~

~~aggregates a lot in order to facilitate the steady flooded condition, e.g. to suppress weed growth.~~ We applied a downscale algorithm of national reported CA area values on a subset of rainfed annuals' ~~the CA-suitable~~ cropland area (see Fig. 1 box "Downscaling"; see following Sect. 2.4~~section~~ for more details).~~, so that part of this cropland was assigned either to CA area or checked for soil depth to bedrock again.~~ The remaining rainfed annuals' cropland~~In case of~~ not being ~~included in~~assigned to ~~the~~ CA area ~~again~~ is checked again for ~~and~~ soil depth to bedrock. In case it was shallower ~~lower~~ than 20 cm, the cropland was as well assigned to reduced tillage, assuming less depth, frequency, mixing efficiency, or alternative cultivation practices. ~~or in case of~~In case of soil depth to bedrock of 20 cm or more ~~enough soil depth~~ ~~it~~the remaining cropland ~~was~~ depending on crop type was either mapped to the conventional annual or to the rotational tillage system.



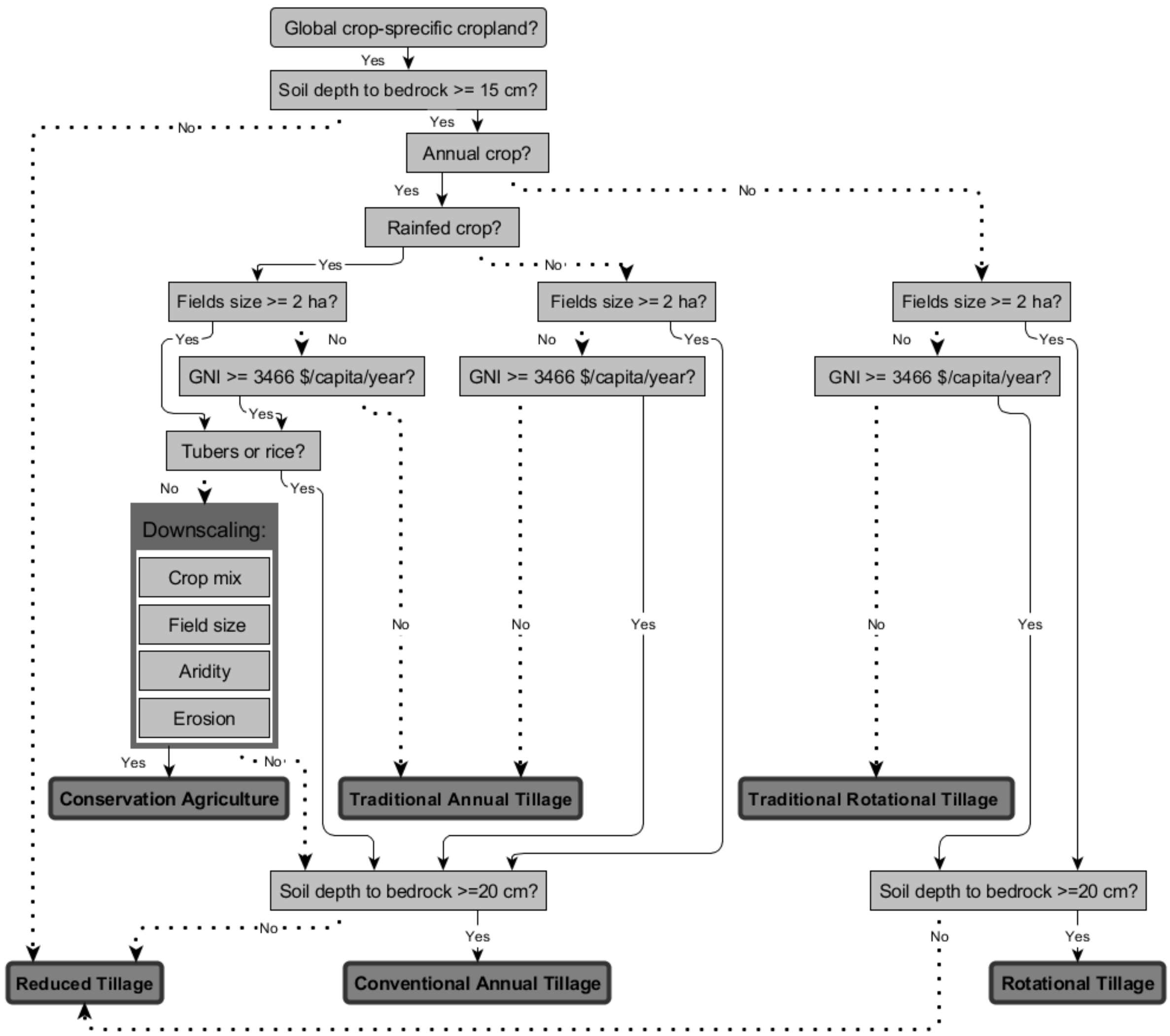


Figure 1: Decision tree for allocating cropland ~~(ha)~~ to six derived tillage systems. The data processing and mapping was pursued as depicted from top to bottom of the diagram. Each box represents a check on a grid cell whether reporting values from the different data layers meet the derived thresholds or specific cropland features. The arrows with solid lines indicate a 'yes' and arrows with dotted lines a 'no' in the allocation procedure of crop-specific area to tillage systems. The box indicating the 'Downscaling' represents our probability and suitability indicators applied to downscale national CA area values ~~(ha)~~ to a spatially heterogeneous pattern at ~~sub-national scale~~ per grid cell. Boxes with darker grey background shading and thicker frames show the derived types of tillage systems. (Abbreviation of Gross National Income as: GNI)

2.4 Downscaling reported national CA area to the grid cell

2.4.1 Mapping rules for downscaling CA

Generally it can be assumed that the entire cropland is suitable for some kind of sustainable farming technique but in the following we refer to 'potential CA area' as the area where we regard the adoption of CA as more likely than for the remaining cropland where CA adoption would require additional assistance or support for the farmer. ~~Cropland considered to be suitable for~~Potential CA area is derived from the ~~rainfed~~ cropland ~~area of these~~ 22 rainfed annual crops ~~(Table S2)~~ in grid cells reporting dominant large ~~dominant~~ field size ~~as 'large'~~ in low income countries ~~and~~ and all field sizes in high income countries. Cropland areas of ~~–~~ annually planted rainfed crop types were considered as suitable for CA practice following the finding of Kassam et al. (2009) who state, that much of the CA development to date has been associated with rainfed arable crops. We selected the following annual crop types reported by SPAM2005 as suitable for CA in this study: barley, beans, chick peas, cotton, cowpea, groundnut, lentil, maize, other cereals, other pulses (e.g. broad beans, vetches), pearl millet, pigeon ~~-~~pea~~s~~, rapeseed, rest (e.g. spices, other sugar crops), sesame~~-~~seed, small millet, sorghum, soybean, sunflower, tobacco, vegetables (e.g. cabbages and other brassicas), and wheat (see Table S2) following Giller et al. (2015)'s findings on CA-suitability ~~for~~ of (dryland) grain crop types. All annual rainfed root, tuber, and rice cropland is excluded from the potential CA area following Pittelkow et al. (2015), who reported larger yield penalties for these crop types when applying no-tillage practices. Rice is often produced as paddy rice, requiring puddling, which is a practice modifying the soil aggregates a lot in order to facilitate the flooded condition, e.g. to suppress weed growth. A conversion from puddled to dryland rice production as well as improved drainage of tuber crop~~s~~ production area may require additional management steps by the farmer in order to achieve comparable yield levels with no-tillage as under conventional production methods. ~~Cropland considered to be suitable for CA is derived from the rainfed cropland area of these 22 annual crops (Table S2) in grid cells reporting dominant field size as 'large' and all field sizes in high income countries.~~ The resulting ~~CA-suitable~~ potential CA area amounts to 4.65 Mkm^2. ~~From that CA-suitable area data layer we computed the input variable "crop mix" as the ratio of the sum of 22 CA-suitable crop types' areas over the sum of total cropland area per grid cell.~~

As stated by Powlson et al. (2014) for the Americas and Australia, by Rosegrant et al. (2014) in general on no-tillage, by Scopel et al. (2013) for Brazil on CA, and by Ward et al. (2018) on CA, largest adoption rates of minimum soil disturbance management principles can be found on medium to large farms. There is ~~few~~ low adoption of CA or no-tillage among small-scale farms, with the exception of Brazil (Rosegrant et al., 2014), where adoption of CA was~~is~~ ~~promoted~~ supported through policies and technological investments.

We developed a linear regression with the 'stats' package of R (R Development Core Team, 2013), applying the linear correlation model ('lm function') to assess the statistical relation between national average farm size (Lowder et al., 2014) and percentage share of CA area (FAO, 2016) on arable land~~ in 2005~~. The functional relation exhibits an increase in the national share of CA on arable land with an increase of~~in~~ average farm size over the country sample (Fig. S3).

Based on the literature findings and regression results, we assumed that no-tillage in the context of CA was highly probable for cropland in grid cells with large fields (~~,~~here serving as a spatial proxy for large farm size and mechanization).

Furthermore, we considered no-tillage as suitable for arable production under arid conditions (Kassam et al., 2009; Pittelkow et al., 2015), because of less aeration,~~ and~~ more stable pores and soil aggregates compared to soils managed with conventional tillage. In CA systems, the evapotranspiration is additionally reduced by a continuous biomass cover of at least 30% of the soil surface, which promotes yield stability in drought prone production environments.

As a last allocation criterion, CA was regarded as suitable for crop production in areas with elevated erosion levels. Basso et al. (2006) ~~state~~find~~,~~ that farmers may make use of ~~the~~ green or residue cover to protect the soil surface during high intensity rainfall events. Our mapping rule also is in line with the finding of Kassam et al. (2009) stating that wind and water erosion were major drivers of CA adoption in Canada, Brazil, and the USA. According to Schmitz et al. (2015) and Govaerts et al. (2009), also Asian and African agricultural producers could benefit from the positive effects of CA in erosion prone areas. ~~Here the corresponding mapping approach was to assume increased probability of CA practices in cells which report water erosion values exceeding 12 t ha^{-1} year^{-1} as the upper bound of the soil loss tolerance value (T-values) defined by the USDA (Montgomery,~~

~~2007). This assumption also is in line with the finding of Kassam et al. (2009) stating that wind and water erosion are major drivers of CA adoption in Canada, Brazil, and the USA. According to Schmitz et al. (2015) and Govaerts et al. (2009), also Asian and African agricultural producers could benefit from the positive effects of CA in erosion prone areas.~~

2.4.2 Logit model for downscaling national CA

Cropland, field size, ~~We used w~~water erosion, and aridity~~, field size, and crop mix~~ data per grid cell are used as ~~spatial~~ predictors determining the spatial distribution of national reported CA area within a country (Fig. S4.1-4). We developed a logit model to transform and combine ~~values of~~ these four spatial predictors ~~variables~~ into probability values per grid cell, indicating the likelihood of CA area occurrence~~ per grid cell~~. ~~We chose t~~The logit model was chosen because different ranges of the spatial predictor datasets are made comparable at equal weights without losing much detail. ~~With the help of the logistic regression we deduce the probability of a grid cell to contain CA area as a probability value between 0 and 1.~~

From the potential CA area data layer we computed the input variable "crop mix" as the ratio of the area sum of 22 CA-suitable crop types over the sum of total cropland area per grid cell. We ~~applied the spatial predictor crop mix~~ assum~~eing~~ an increasing probability for CA area occurrence in grid cells~~,~~ with increasing cultivated area share of CA-suitable crops types. This was based on the assumption~~s~~ that cropland within a grid cell belongs to one management regime, under which rotations with CA-suitable crops are practiced, and a similar set of soil working equipment is employed. The~~se~~ assumptions also takes into account peer group influence and knowledge spillover effects from early adopters of a new technology (here CA practice) towards their neighbors (Case, 1992; Maertens and Barrett, 2013).

Regarding the statistical relation between farm size and CA adoption, we assume that the larger the field size, the higher the CA probability especially for field sizes equal or larger 2 ha depending on the income level of a country, taking 2 ha as the midpoint of the transformed field size logit curve.

We set missing water erosion values in grid cells reporting potential CA area to the neutral value of 12 t ha^{-1} $year^{-1}$, since it depends on very small-scale conditions, e.g. slope. ~~We set missing erosion values in grid cells reporting CA-suitable cropland area to the neutral value of 12 t ha⁻¹ year⁻¹, since it depends on very small-scale conditions, e.g. slope.~~ When transforming the water erosion values to logit, we ~~also~~ set 12 t ha^{-1} $year^{-1}$ as the midpoint value of the function. Here the corresponding mapping approach was to assume increased probability of CA practices in cells which report water erosion values exceeding 12 t ha^{-1} $year^{-1}$ as the upper bound of the soil loss tolerance value (T-values) defined by the USDA (Montgomery, 2007).

The midpoint of aridity's logit regression curve is chosen at 0.65 resulting in higher probabilities of CA area occurrence for grid cells reporting arid (values smaller than 0.65) than humid (values larger than 0.65) growing conditions. We interpolated missing aridity values in grid cells where SPAM2005 reports cropland, except for one island near Madagascar, which we set to the logit-neutral value of 0.65, because we assumed very special climatic conditions there.

~~We interpolated missing aridity dataset where SPAM2005 reports cropland, except for one island grid cell value near Madagascar, which we set to the logit-neutral value of 0.65, because we assume very special climatic conditions there.~~

We tested for (Pearson) correlation among the four spatial predictor variables with the R 'base' package (R Development Core Team, 2013), in order to prevent autocorrelation effects (Table 3).

(Table 3)

Generally correlation coefficients (r) among the datasets are low and mostly negative, except for field size and crop mix.

Those four cropping system indicators are used as explanatory variables in the regression to get the probability of cropland in a grid cell to be CA area as a value between 0 and 1. The probability of CA in a grid cell is derived via the following Eq. (1):

$$CA_{Grid\ cell} = \frac{1}{1+\exp\left(-\sum_{i=1}^{4} k_i\,(vx_i - xmid_i)\right)} \quad (1)$$

w~~W~~here, i represents the input datasets of water erosion, aridity, crop mix, and field size (proxy for farm size), k_i refers to the slope value, $xmid_i$ to the central points of each of the logit curves, and vx_i to grid cell values of the referring input dataset.

A sensitivity analysis has been conducted to assess the explanatory power of each of the four input variables ~~(Fig. S5)~~and the uncertainty of our parameter set and combination (Fig. S5). First step was to vary our chosen reference slope (k_i) of each of the input dataset values by factors of 2 and 0.5 (+100%, -50%), as a next step each of the variables is dropped, and finally each of the variables is used ~~as the only variable~~single in the logit model. The sensitivity test was conducted at the global scale and also for each of the 54 CA reporting countries.

2.4.3 Mapping CA area per country

The~~Our~~ downscaling of total national CA area values comprise~~s~~d subsetting all grid cells with CA-suitable area per CA area reporting country (FAO, 2016). T~~and t~~hen these grid cells were sorted~~ing~~ in ~~these grid cells per~~ decreasing order according to their CA probability values derived with the logit equation. As a next step, ~~we select~~ grid cells with the highest ~~top most~~ logit model results were selected step wise while adding up the corresponding~~ir~~ potential CA area~~-suitable cropland~~ until the reported national CA area threshold was~~is~~ reached. We receive~~d~~d a heterogeneous pattern of allocated CA area at 5 arc-minutes resolution grid within a CA reporting country, according to the likelihood of CA area occurrence based on ~~our~~ the logit results, ~~and on our~~ statistical data, and literature findings. ~~Similar to the 'bottom-up scenario' of Prestele et al. (2018), we deduce potentially CA-suitable area, specifying the socio-economic and biophysical extent of possible CA adoption with respect to crop mix, field size, aridity, and erosion analyzed within this study. We add the subset of 22 annual rainfed crop-specific areas under reduced tillage in grid cells reporting soil depth to bedrock lower than 15 cm, to the CA-suitable area generated.~~

2.4.4 Scenario CA area ~~Area potentially suitable for CA~~

Similar to the 'bottom-up scenario' of Prestele et al. (2018), we deduced 'scenario CA area' indicating the maximum area extent of CA adoption~~potentially CA-suitable area~~, under assessed current ~~specifying the~~ socio-economic and biophysical conditions~~extent of possible CA adoption with respect to crop mix, field size, aridity, and erosion analyzed within this study~~. We add the subset of 22 annual rainfed crop-specific areas in grid cells with large field sizes in low income and all field sizes in high income countries from ~~under~~ reduced tillage

~~in grid cells reporting soil depth to bedrock lower than 15 cm~~ to the potential CA~~-suitable~~ area to calculate scenario CA area per grid cell.~~ generated~~

~~Similar to the ‘bottom-up scenario’ of Prestele et al. (2018), we deduce potentially CA-suitable area, specifying the socio-economic and biophysical extent of possible CA adoption with respect to crop mix, field size, aridity, and erosion analyzed within this study. We add the subset of 22 annual rainfed crop-specific areas under reduced tillage in grid cells reporting soil depth to bedrock lower than 15 cm, to the CA-suitable area generated.~~

~~3 Tillage systems per grid cell~~

3 Spatial pattern of six tillage systems

We allocated global cropland of SPAM2005 to the six tillage systems at a spatial resolution of 5 arc-minutes according to a set of rules (Table 4~~Figure 1~~). In terms of area~~s~~, conventional (Fig. 2) and traditional annual tillage (Fig.3) globally constitute the most widespread tillage practices. Both systems are applied for annual crops, which are globally growing on~~occupy~~ the largest cropland fraction, are traded, and consumed most. Large parts of the cropland under traditional annual tillage for rainfed and irrigated annuals, is located in South East Asia, with especially high cropland area shares in India followed by Sub-Saharan Africa, and then South America (Table S9 for aggregated tillage system areas to country scale). Conservation Agriculture globally constitutes the third largest tillage system area (Table 4 and following Sect. 3.1). Rotational tillage (Fig. 4) is on the fourth position in the ranking of tillage system areas followed by traditional rotational tillage area (Fig. 5). Most traditional rotational tillage system area can be found across the tropical region of South-Eastern Asia and West Africa. Reduced tillage has the smallest area extent (Table 4) ~~whereas~~which we find mostly ~~referring cropland~~ in a narrow band between 10° and 20° Northern latitude (Fig. 6). It occurs in Mexico, South of the Sahel region but mostly is found on cropland in India (Table S8 for further metrics across tillage system areas; Table S9).

(Table 4)

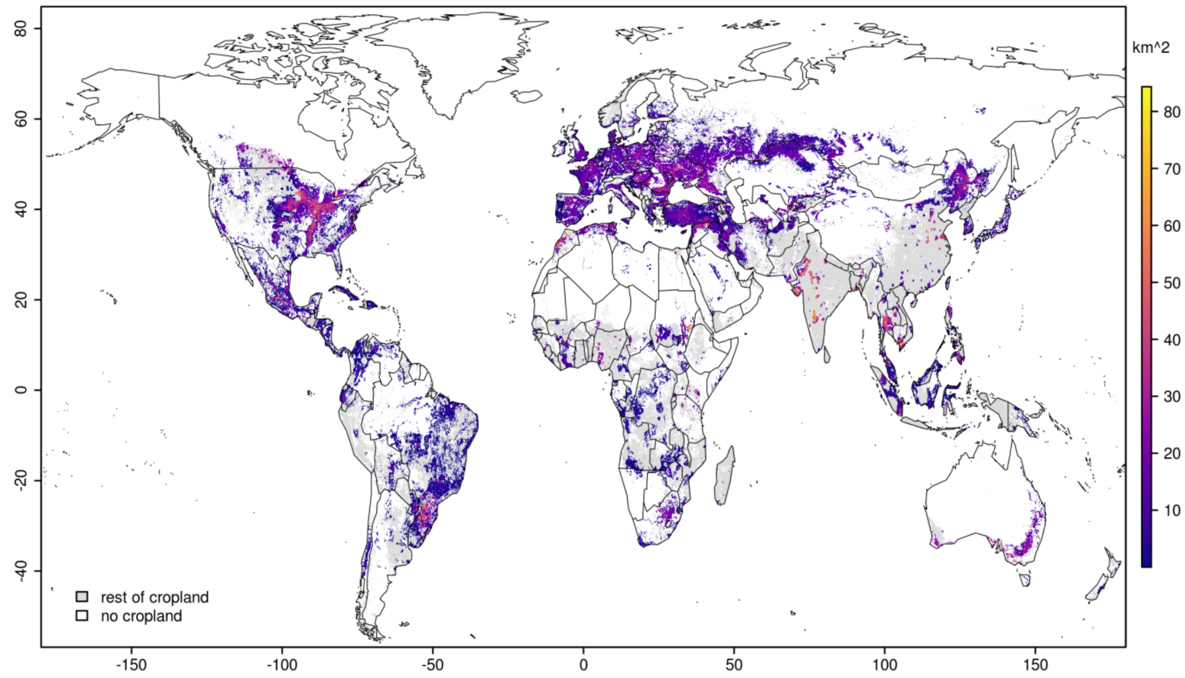


Figure 2: Conventional annual tillage area, which has been allocated to the majority of global physical cropland area.

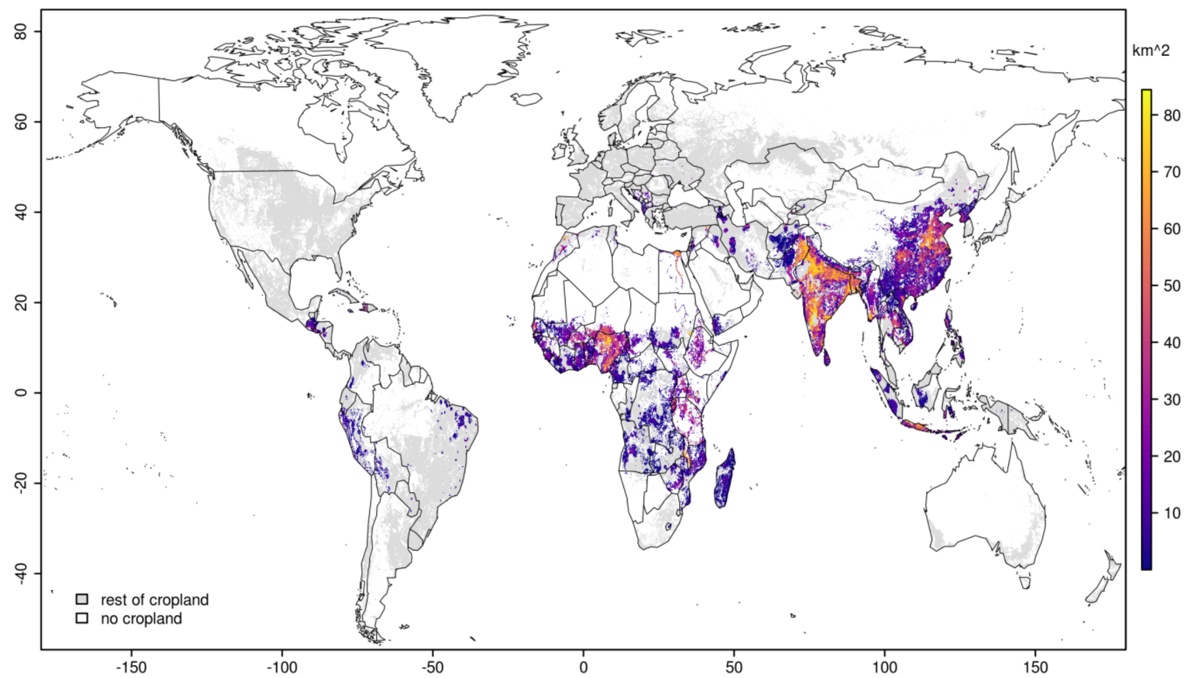


Figure 3: Traditional annual tillage area as sums over 29 annual crop types' areas in grid cell reporting dominant field size smaller than 2 ha and in countries classified as low income in this study.

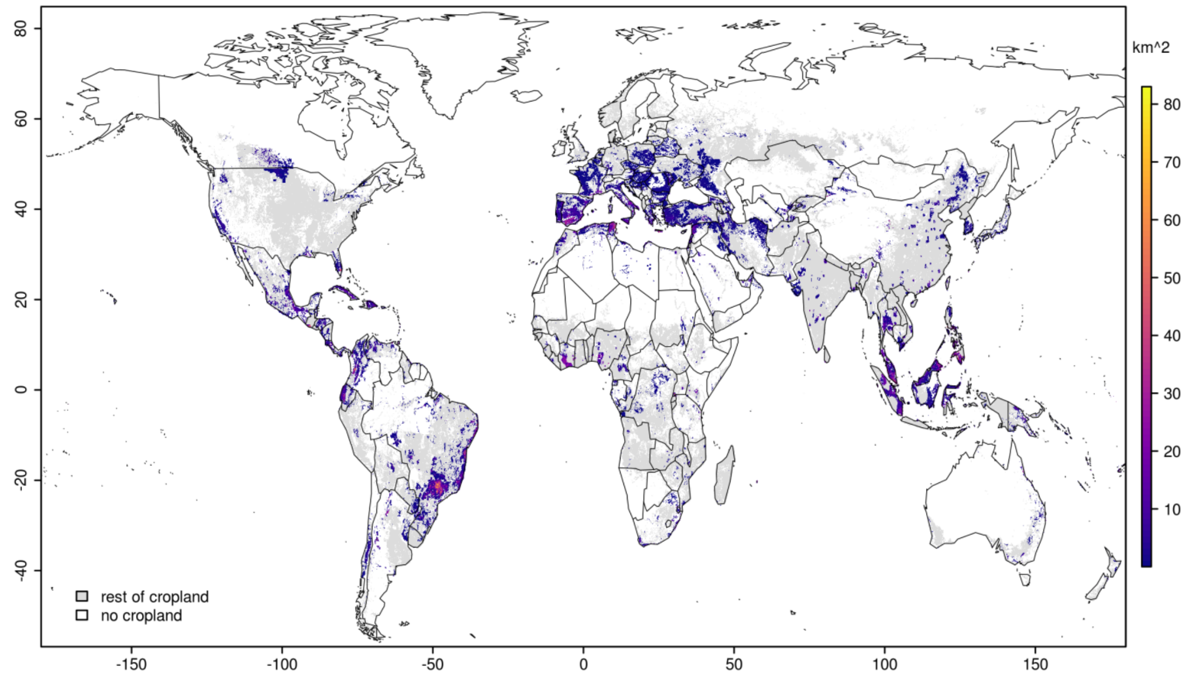


Figure 4: Rotational tillage area on cropland area of 13 perennial crop types in grid cells with dominating field sizes of minimum 2 ha or larger in low income or all field sizes in high income countries.

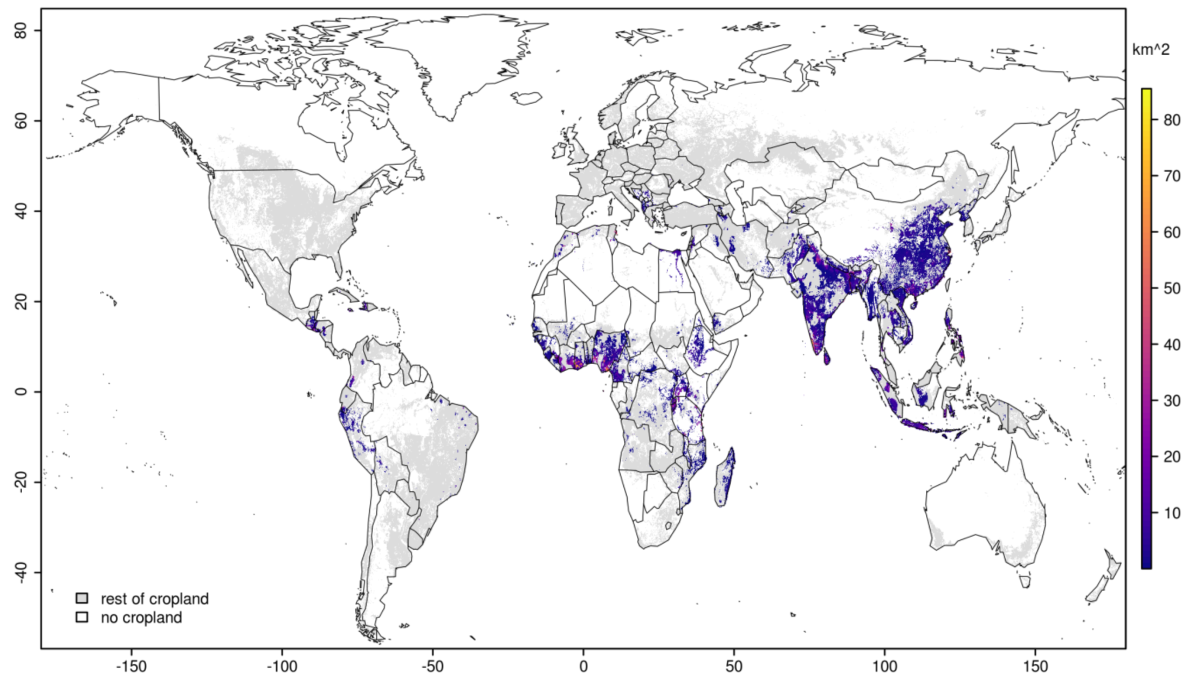


Figure 5: Traditional rotational tillage area as cropland of 13 perennial crop types in grid cells characterized by field sizes smaller than 2 ha in countries considered as low income in this study.

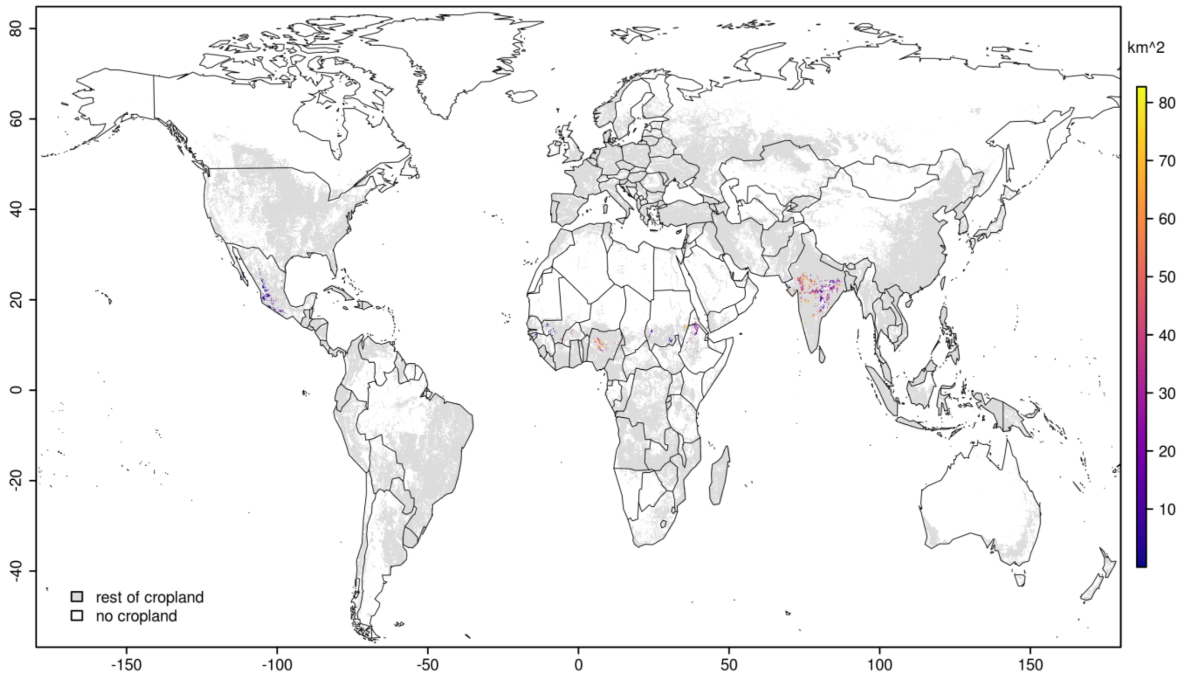


Figure 6: Reduced tillage area where soil depth to bedrock is limiting the depth of tillage.

3.1 Conservation Agriculture area

3.1.1 The results of the logit model

We deduced the likelihood of CA area in a grid cell via the logit model approach according to the indicators crop mix, field size, water erosion, and aridity (Fig. 7~~2~~). The geographical pattern of the logit results (further referred as ref-logit) exhibits higher probabilities for cropland in grid cells outside the tropical climate zone and in rather continental regions. Probability of CA is higher for cropland in grid cells reporting large field sizes which are mostly found in developed and land-rich countries, i.e. in the USA, Australia, and large parts of Europe. Grid cells in the tropics receive rather low logit results due to their humid conditions, smaller field sizes, lower income levels, and crop types cultivated. In India, China, and Pakistan the majority of cropland ~~was exclude from~~ showed very low CA likelihood ~~suitability~~.

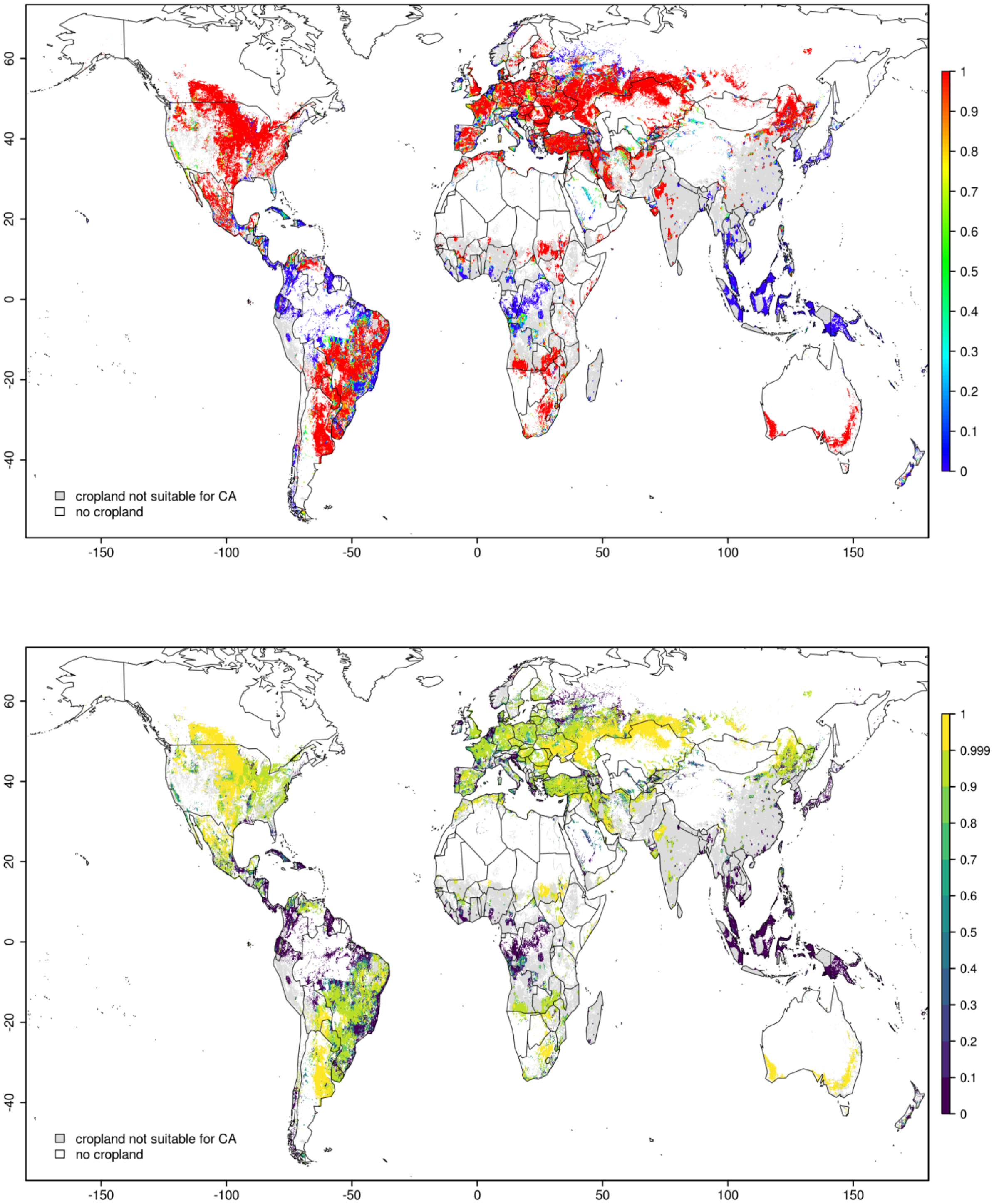


Figure 7:~~2~~ Probabilities of Conservation Agriculture area per grid cell with high values as ~~red~~ green to yellow and low ones in blue to purple colors (white color indicates the absence of cropland, and grey the cropland (IFPRI/IIASA, 2017b) ~~reported by SPAM2005~~ which is excluded from the ~~area considered suitable for CA~~potential CA area due to soil depth, crop type, irrigation, field size, or income level).

3.1.2 Results of the sensitivity analysis of the logit model

The sensitivity analysis of ~~our~~ the logit model shows mixed responses to ~~our~~ the perturbations of slope or variable combination ~~in the logit model~~ (Table 54, Fig. S5). Rank correlation (r) to the ref-logit is much lower when taking one variable only compared to each of the other drop-variable settings or slope modifications. Regarding modifications of the slope parameters of the input variables, we calculated the lowest rank correlation coefficient for increasing the slope of aridity by +100 % and for decreasing the slope of crop mix by -50 % compared to changing the slopes of the other three variables respectively.

Erosion has lowest explanatory power as can be interpreted from the very high correlation coefficient to ref-logit when dropping it - but even negative correlation when taking it into the logit equation only.

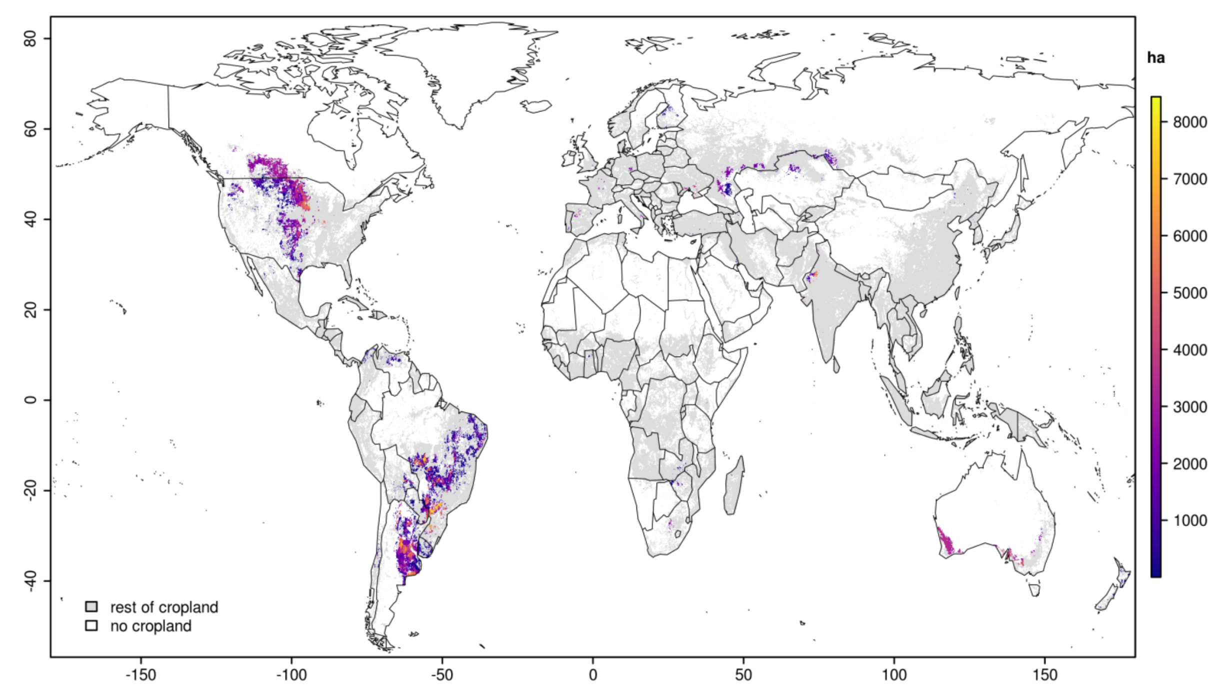
This ~~Our~~ finding is in line with the findings of the sensitivity tests performed by Prestele et al. (2018) who find erosion as the variable with the smallest explanatory power as well.

Crop mix has the largest explanatory power in the logit equation as shown by the lowest correlation coefficient value when dropping it but highest when taking that variable only (Table 5~~4~~). We additionally report on the sensitivity results for the 54 CA reporting countries, where the effects of slope and variable perturbation show very different patterns per country (Table S6). However, as national CA areas are allocated within individual countries, the sensitivity of ranking within countries is of greater importance than the global rank correlation.

(Table 5~~4~~)

3.1.3 Downscaled CA area

Total downscaled CA area (1,101,899 km^2~~110,190,763 ha~~, Fig. 3~~8~~) is slightly lower than FAO reported total CA area ~~of~~ for these countries (1,102,900 ~~110,289,988 ha~~km^2). This difference occurs because of our algorithm, which assigned the entire CA-suitable cropland area per grid cell to CA, taking the cropland of the following grid cell in or out of consideration striving for least deviation from the threshold per country (Table S7 for comparison of reported and downscaled country values). A further difference is due to the insufficient potential CA area in North Korea and New Zealand, resulting in the fact that only part of the national reported CA area could be allocated to.



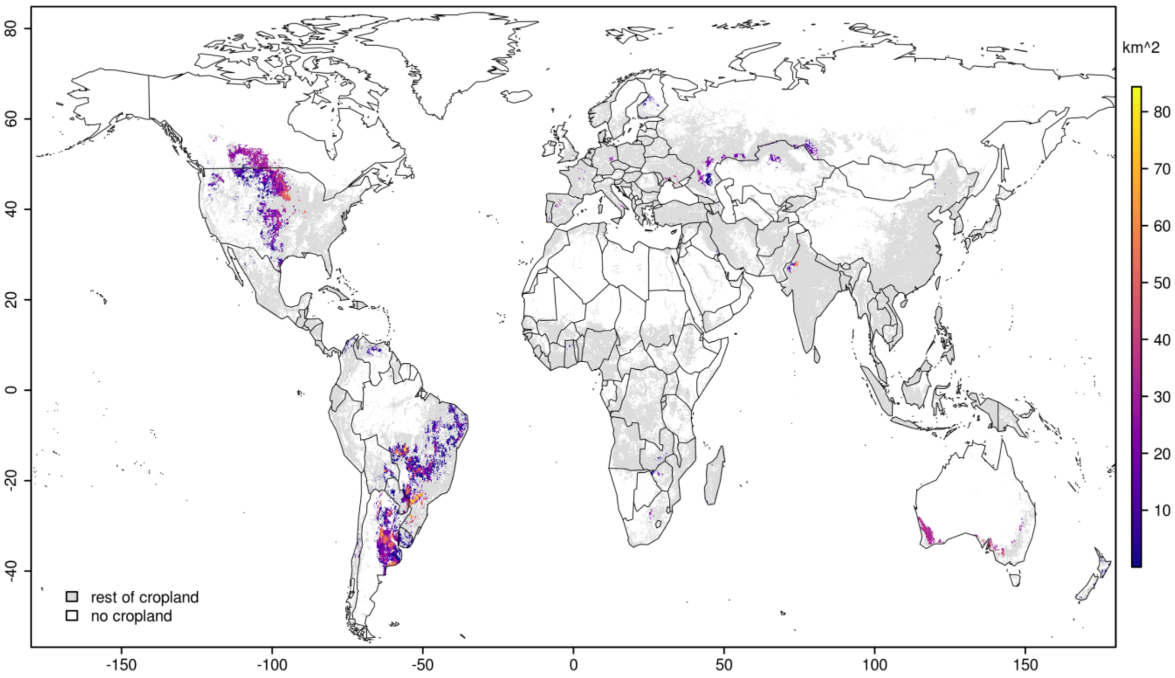


Figure 8:~~3~~ Downscaled Conservation Agriculture area (km2~~ha~~) (colored) on total cropland (grey) per grid cell for 54 reporting countries around the year 2005.

Aggregated crop-specific CA area values reveal that most downscaled CA area was allocated to ~~CA-suitable~~ area cultivated with soybean, followed by wheat, and then maize (Table 6~~5~~). These three crops are among the most important produced, traded, and consumed agricultural goods, making their production highly competitive and therefore the incentive to reduce operational costs (e.g. regarding tillage~~ operation~~) is high. Another reason for soybean and maize being among the crops mostly produced under CA, may be the usage of high yielding, or genetically modified crops, coming along with improved pesticide resistances, which make them more suitable for possible herbicide applications (Giller et al., 2015) replacing tillage operations on-field. In Argentina, soybeans are found to be the most common plant cultivated under CA with usually lower residue coverage than required for being a CA system (Pac, 2018). Subsistence farming crops, e.g. peas and millet, were contributing only few cropland to the downscaled CA area (Table 6~~5~~), because they are more drought resistant (Jodha, 1977), and of rather regional importance in terms of food security while being traded less on the international markets (Andrews and Kumar, 1992).

(Table ~~5~~6)

3.1.4 Scenario ~~Crop specific area potentially suitable for~~ CA area

We deduced the total global potential CA~~-suitable~~ ~~cropland~~ area of 4.65 Mkm² (see above). Additionally, we identified 0.02 Mkm² of 22 rainfed annual crop types' areas on large fields in low income countries and all field sizes or in high income countries from the reduced tillage system area, which potentially could be converted to CA area as well. We calculated a total ~~potentially~~ scenario CA~~-suitable~~ area of 4.67~~6~~ Mkm², where perceived driving forces, e.g. CA adoption supporting agricultural policies, targeted mechanization efforts, and knowledge dissemination approaches could lead to an area expansion of CA practices.

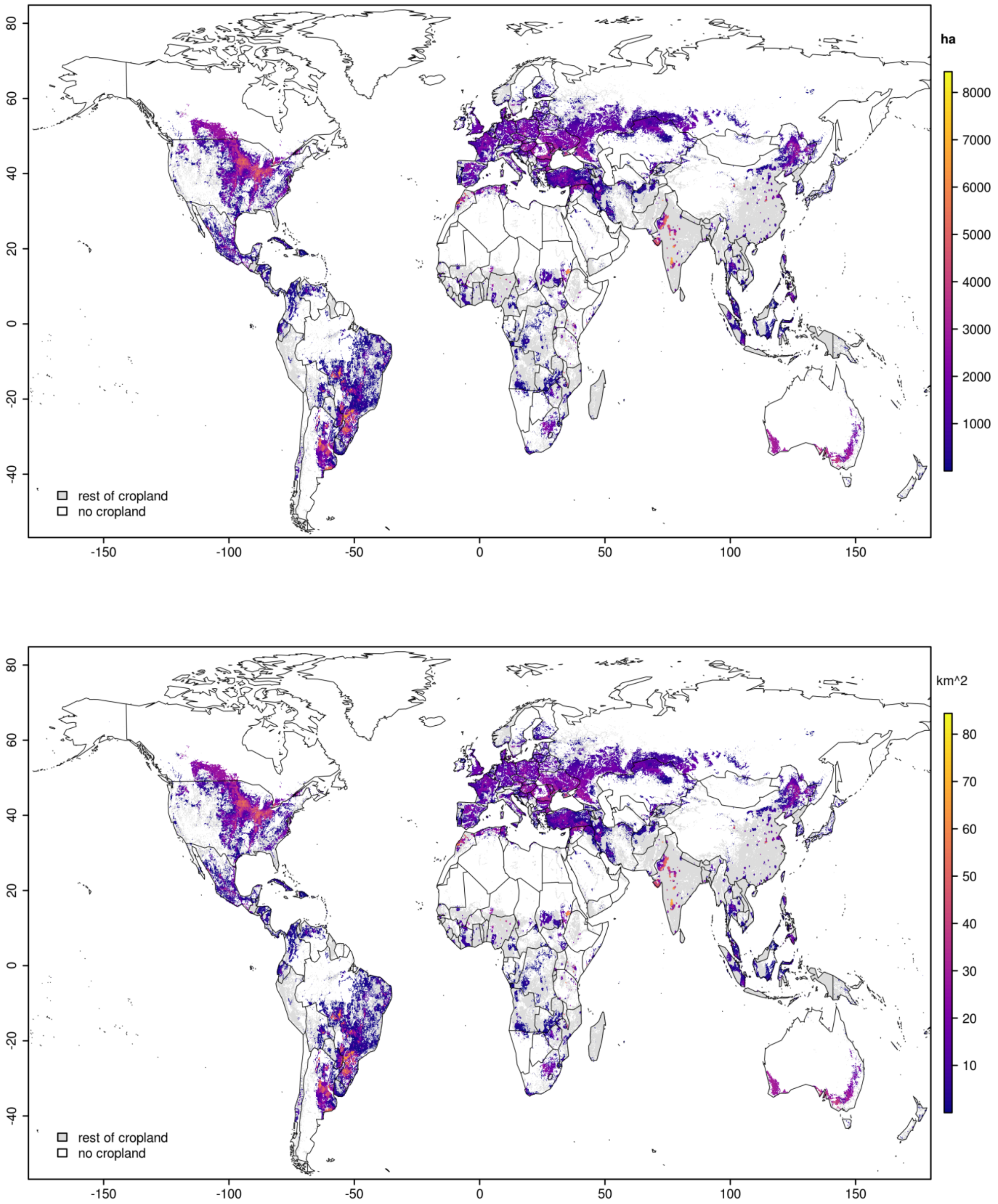


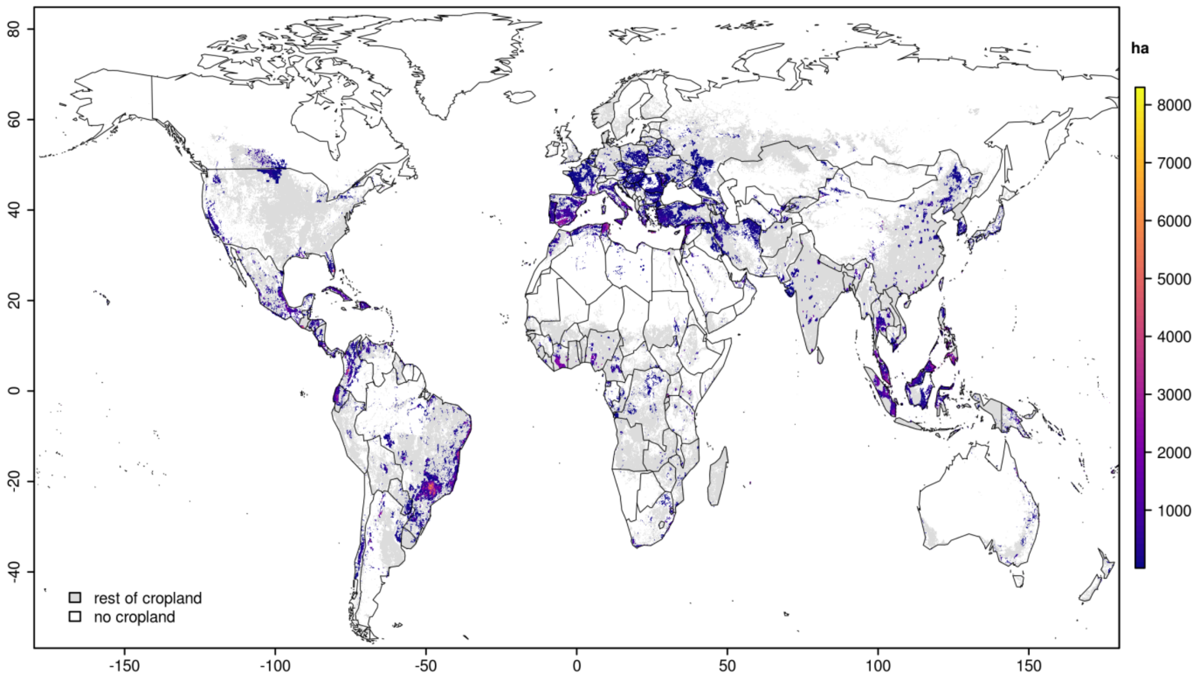
Figure 9:~~4~~ Scenario ~~Area potentially suitable for~~ Conservation Agriculture area (km2) (colored) on total cropland (grey) per grid cell.

~~3.2 Globally total areas and regional pattern of tillage systems~~

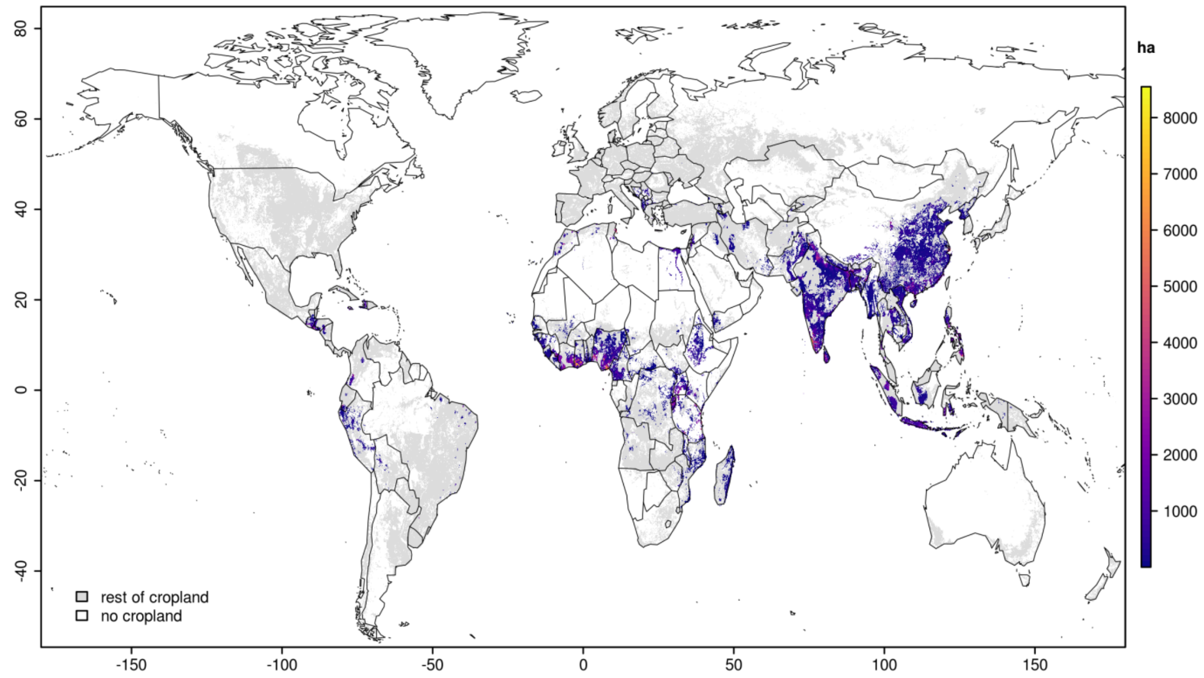
~~We allocated global cropland of SPAM2005 to the six tillage systems at a spatial resolution of 5 arc-minutes according to a set of rules. In terms of areas conventional and traditional annual tillage globally constitute the most widespread tillage practices (Table 6). Both systems are applied for annual crops, which globally occupy the largest cropland fraction, are traded, and consumed most. Large parts of the cropland under traditional annual tillage (Fig. 7) for rainfed and irrigated annuals is located in South~~

~~East Asia, with especially high cropland area shares in India followed by Sub-Saharan Africa, and then South America (Table S9 for aggregated tillage system areas (ha) to country scale). Conservation Agriculture constitutes the third largest tillage system area globally. Rotational tillage is on the fourth followed by traditional rotational tillage on the fifth position in the ranking of tillage system areas (Fig. 5 and 6). Most traditional rotational tillage system area can be found across the tropical region of South-Eastern Asia and West Africa (Fig. 6). Reduced tillage has the smallest area extent (Table 6) whereas we find most referring cropland in a narrow band between 10° and 20° Northern latitude (Fig. 9). It is spread in Mexico, African countries Southern to the Sahel zone but mostly found on cropland in India (Table S8 for further metrics across tillage system areas; Table S9).~~

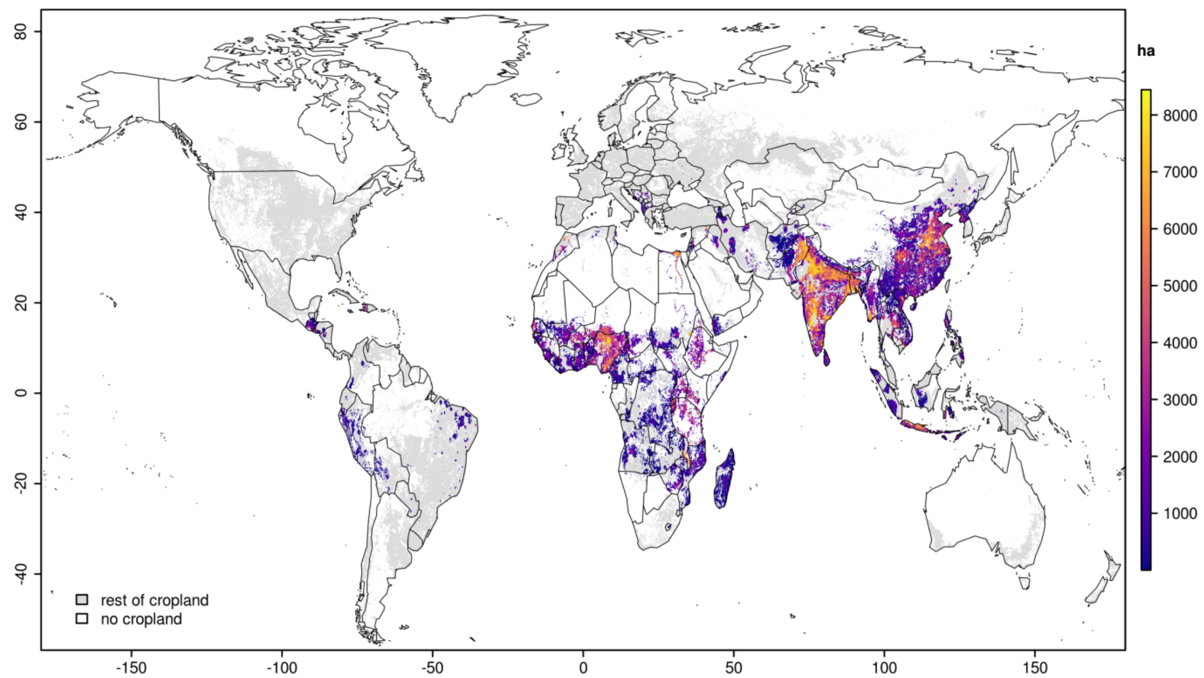
~~(Table 6)~~



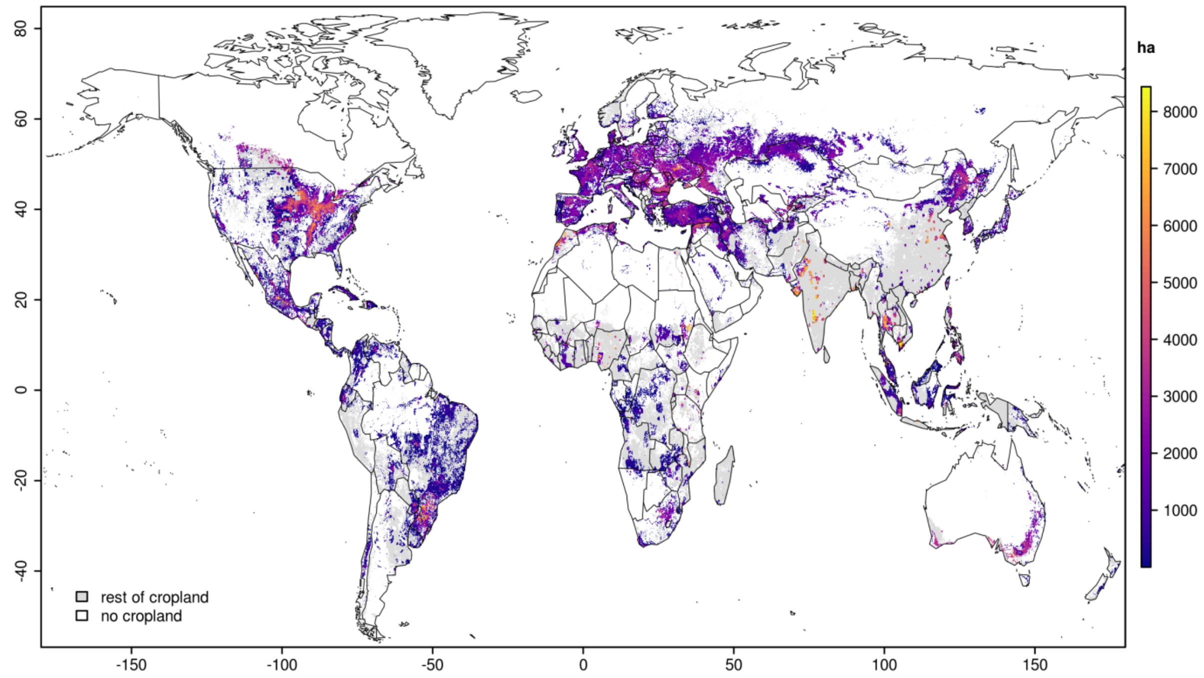
~~**Figure 5 Rotational tillage area on cropland area of 13 perennial crop types in grid cells with dominating field sizes of minimum 2 ha or larger in low income or all field sizes in high income countries.**~~



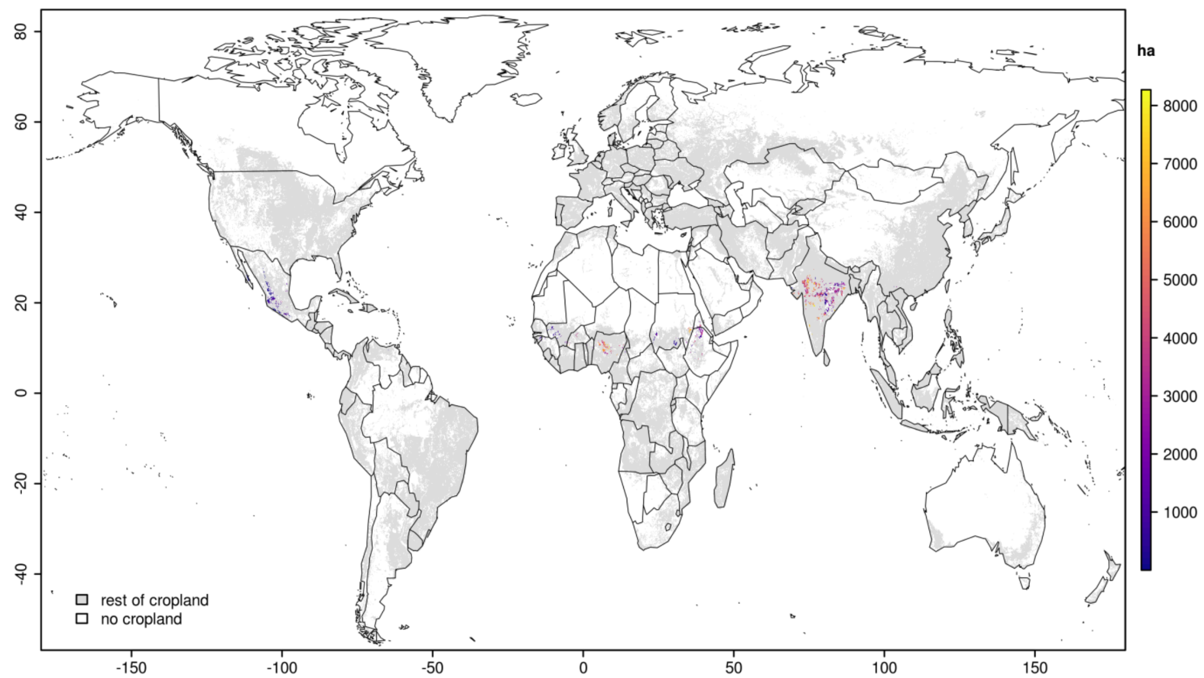
~~**Figure 6 Traditional rotational tillage area as cropland of 13 perennial crop types in grid cells characterized by field sizes smaller than 2 ha in countries considered as low income in this study.**~~



~~**Figure 7 Traditional annual tillage area as sums over 29 crop types' areas in grid cell reporting dominant field size smaller than 2 ha and in countries classified as low income in this study.**~~



~~**Figure 8 Conventional annual tillage area, which has been allocated to the majority of global cropland area.**~~



~~**Figure 9 Reduced tillage area mapped to grid cells reporting soil depth to bedrock shallower than 20 cm, so unsuitable for deep mechanized tillage.**~~

4 Discussion

4.1 Comparison of results to other studies

In the absence of alternative tillage area datasets for validation at the global scale we here want to discuss the way our tillage system area results relate to other studies’ findings.

We compare the spatial pattern of our added traditional tillage system area to the one reported by the cropland subsets of SPAM2005 for low input and subsistence ~~farming~~production. According to You et al. (2014), both ~~are~~ production levels are characterized by a low level of mechanization or rather manual labor and low input usage. The sum of our traditional tillage systems’ (rotational and annual) areas (4.63 Mkm^2) is slightly higher than the sum of SPAM2005 subsistence and low input technological level cropland (4.55 Mkm^2). We deduced more traditional tillage system area in South-East Asia, Sub-Saharan Africa, and Peru than SPAM2005 reported under low and subsistence farming (see difference map in Fig. S10). Further comparison reveals a moderately lower amount of area under traditional tillage in our dataset for Europe, the Near East, South America, and Australia, i.e. in countries which are regarded as emerging or developed economies. The spatial difference may be due to the fact that SPAM2005 is a product of a sub-cell cross-entropy optimization approach to distribute cropland of the same crop species into several production levels per grid cell. Contrary to this, we used the field size and gross-national income as spatial indicators for un-mechanized tillage systems by masking out cropland either per entire grid cell or country-wise according to our derived thresholds. We calculated the spatial correlation via a regression of the added area values of our traditional tillage system and of the sum of low input and subsistence production level cropland reported by SPAM2005. We found a regression factor (r^2) of 0.54 ($p < 0.001$, slope of 1.139) among both datasets’ ~~grid cell specific area~~ values.

Our estimate of traditional tillage system area in turn is lower than the finding by Lowder et al. (2016), stating 5.87 Mkm^2 to be under management of farms smaller than 2 ha size (~12 % of their arable cropland assumption). ~~Deviations between the estimates might evolve from our chosen threshold of 2 ha on the field size dataset to distinguish small from large field sizes.~~

In order to compare our results to the findings of Erb et al. (2016) on tillage intensity areas, we added up our reduced, both rotational tillage system areas, and the downscaled CA area to represent the ‘low intensity’ tillage area, ~~and~~ whereas conventional and traditional annual tillage are summed up to the ‘high intensity’ tillage area. Since the description of what is included in their ‘low intensity’ area is inconsistent within their main text, tables, and ~~their~~ supplementary information~~s~~, we state two different estimates of our results - both exhibiting different absolute values and shares compared to the findings of Erb et al. (2016) (Table 7).

(Table 7)

We additionally pursued a provincial and state level comparison between our downscaled CA area to reported no-tillage area values for Canada, Brazil, and Australia (Fig. and Tables S11), because these countries are among the top four adopters of CA (see Table S7). CA area values from AQUASTAT (FAO, 2016) for these three countries were dated 2006, 2005, and 2006 and compared to reference reporting years of 2006, 2007-08, and 2006 respectively. Although this provides a comparison to independent data, it cannot be considered as a validation because of the temporal mismatch among compared datasets and aggregation uncertainty when using Global Administrative Areas (2015) for aggregating tillage areas to sub-national scale. For each of the selected countries our downscale algorithm can quite well reproduced the main no-tillage area but tends to too strongly concentrate ~~allocate too much~~ CA area in some regions instead of a more homogenous spread, as observed in the associated reference maps.

Prestele et al. (2018) analyzed CA area time series data by FAOSTAT and have found an increasing trend of CA adoption within countries and to more countries since the 1970s. Thise trend is likely going to continue as farm holdings increase in size while decreasing in number in upper middle and high income countries (Lowder et al., 2016). At the same time, the adoption rate of CA in smallholder farming systems in low income countries (e.g. in Sub-Saharan Africa) may persist low~~ in~~, where average farm size reveals a decreasing trend (Jones, 2017). Adoption of CA practices by smallholder farmers is hampered by competition for residue use (Scopel et al., 2013), missing knowledge, as well as~~and~~ restricted access to inputs and financial capital (Kassam et al., 2009) making them more risk-~~-~~averse towards adoption of new technology than large-~~-~~scale farmers (Schmitz et al, 2015).

~~We additionally pursued a provincial and state level comparison between our downscaled CA area to reported no-tillage area values for Canada, Brazil, and Australia (Figures and Tables S11), because these countries are among the top four adopters of CA (see Table S7). Although this provides a comparison to independent data, it cannot be considered as a validation because of temporal mismatch among compared datasets and aggregation uncertainty when using Global Administrative Areas (2015) for aggregating tillage areas to sub-national scale. For each of the selected countries our downscale algorithm can quite well reproduce the main no-tillage area but tends to allocate too much CA area to certain regions instead of a more homogenous spread, which spatial pattern can be rather deduced from the associated reference maps.~~

Prestele et al. (2018) state their potential CA area to be 11.3 Mkm² in their 'Bottom–up' and 5.33 Mkm² in their 'Top-down' scenarios until the year 2050. Our estimate of ~~potential~~ scenario CA~~-suitable~~ area of 4.66 Mkm² is lower but of the same magnitude as of their 'Top-down' scenario.~~, despite the differing assumptions and using a slightly different CA mapping approach.~~ Prestele et al. (2018) used another ~~different~~ cropland product,~~t and~~ targeted another time period, pursued a slightly different CA mapping approach, and had different assumptions on the scenario design ~~than we did also~~ which might be causing the main ~~resulting in slight~~ area ~~deviations~~ differences compared to our derived scenario ~~suitable and potentially suitable~~ CA area. In order to take into account, that other modelling groups may applying other cropland inputs than SPAM2005 as presented here, ~~W~~we ~~decided to~~ produced ~~our~~ the tillage dataset and source code flexible in the way that each modeling group may adjust it according to their ~~own default cropland~~ individual crop mix per grid cell~~input~~.

4.2 Potentials, limitations, and implications for applications of the dataset

~~Agricultural land management practices are not only determined by environmental factors, but are embedded in local to regional systems of culture, traditions, and markets. This mosaic of farming conditions can only be taken into account at high spatial resolution. The developed tillage dataset is an attempt to better account for heterogeneous patterns of agricultural management across and within countries by using socio-economic and biophysical data in conjunction. The resolution of the generated dataset with 0.083° is quite high, while most global ecosystem models currently run on 0.5° resolution and may have to aggregate the data for input usage.~~

A limitation to our presented mapping approach is that the input datasets applied cover different time periods, e.g. GLADIS reports water erosion values for approximately the year 2000, SPAM2005 and the field size dataset for the year 2005, the aridity spans to the reference climate data of the period from year 1961 to1990, and for some countries we extracted the only CA reporting year by FAO (2016) from years 2002 up to 2013. By using SPAM2005, field size for 2005, and setting the objected year for the produced tillage dataset to 2005 as well, we tried to minimize inconsistencies in time coverage at least for the cropland ~~data~~extent. GLADIS uses the Global

Land Cover dataset (GLC2000, Bartholomé and Belward (2005)) as land-use information thus reporting water erosion values as an average over the different ecosystem and land-use types per grid cell. Land use as well as land management are results of dynamic socio-economic and environmental processes. Local mismatches in the cropland extents between these datasets might be on the one hand due to abandonment as a result of shifting cultivation or on the other hand due to extension of cropland to converted other land-use types between the years 2000 and 2005. Further mismatches might exist due to different assumptions on~~f~~ crop types and area between different data products. The choice of crop to be cultivated is usu~~s~~ally ~~is~~ taken under consideration~~s~~ of rotations for weed and pest management, household demand, and market conditions together leading to different cropping patterns between the year 2000 and 2005. The aridity dataset does not consider any land-use information but relies on averages of climatic data and parameters.

Another source of uncertainty is the used rule-based approach for mapping the tillage system areas. We statistically proved the relation between national average farm size and CA adoption (S3). Whereas statistical relations between field and farm size can be found in the literature, the mapping rules of distinguishing traditional from mechanical tillage, the suitability of CA for erosion and aridity prone agricultural production environments are based on qualitative literature findings, and ~~exhibit potential~~warrant ~~for~~ further research and scrutiny if new data become available.

The tillage dataset presented here can ~~be assumed to~~ be employed in various applications, depending on the type of model, context, and objective of the user. Agricultural land management practices are not only determined by environmental factors, but are embedded in local to regional systems of culture, traditions, and markets. This mosaic of farming conditions can only be taken into account at high spatial resolution. The developed tillage dataset is an ~~attempt~~effort to better account for heterogeneous patterns of agricultural soil management across and within countries by using socio-economic and biophysical data in conjunction. The resolution of the generated dataset with 5 arc-minutes is quite high. Global ecosystem models are currently mostly run at a coarser resolution than our dataset's resolution and the tillage data may have to be aggregated in such cases. This could introduce further uncertainty to the area under a certain tillage system.

A challenge to~~of~~ the full usage of this dataset is the limited implementation of the 42 crop types reported in SPAM2005 in global ecosystem models. Especially perennial crop types are hardly ever parameterized in ecosystem ~~global biophysical~~ models or if so are rather addressing ~~regional~~ regional-scale applications (Fader et al., 2015). One reason for the missing implementation may be their relatively small cultivation areas globally (~10% of global cropland (Erb et al., 2016)). Woody and other perennial plant species entail ~~interesting~~ potential in the aspect of sustainable agricultural practices because they keep the soil covered for longer periods and thus better protect it from erosive and radiative forces, promote soil organic carbon accumulation (Smith et al., 2008), and stabilize soils more than annually planted crop types.

Another challenge for the application of our tillage dataset in model simulations is the differentiation of soil depth affected by the tillage operation. Some models may be able to differentiate between 20 or 30 cm depth affected by the tillage operation mostly when having a site-based background and therefore a very detailed representation of agricultural management practices (White et al., 2010). The global dynamic ecosystem model LPJ-GUESS and the Community Land Model (CLM) have implemented the tillage routines as a tillage factor accelerating the decomposition rate of the different soil carbon pools (Levis et al., 2014; Olin et al., 2015), so that implementations of spatial variability in depth or mixing efficiency are not straight forward.

White et al. (2010) elaborate on the problem of generally implementing a three dimensional aspect as "surface affected" by the tillage practice, which would be the case for simulating reduced tillage practices as strip-, mulch-, or ridge-till, weed management during the growing period of the main crop, or for preparing the seedbed for inter-cropping cultures. The reduction relates to depth, surface affected or both, for which White et al. (2010) recommend an intermediate model implementation mode which distinguishes two zones, as one share of the soil being affected and the other one not.

Some authors mention partial adoption of CA as referring to the minimal soil disturbance practice only (Giller et al., 2015; Scopel et al., 2013) where residues are not always retained (Pittelkow et al., 2015). This no-tillage practice tries to benefit from saving energy, work hours, machine wearing, and field passes when skipping tillage. No-tillage without a sufficient biological mulch is reliant on the application of increased amounts of herbicides to comply with weeds (McConkey et al., 2012; Mitchell et al., 2012) compared to conventional tillage systems. Leaving the soil unprotected, exposes the soil surface to erosive forces, and enhances nutrient leakage especially under high rainfall intensities. Crusting and compaction of the soil can only be addressed by tilling these fields rotationally, as has been discussed in Erb et al. (2016). This rotational tillage may lead to a decrease of soil organic matter (SOM) due to increased mineralization under aerated conditions and the advantages of not-tilling during the other years disappears (Powlson et al., 2014). The effects of SOM increase under no-tillage only in conjunction with a certain amount of residue inputs, may appear relevant after a transition time of about 10 to 20 years of continuous practice until a new equilibrium state of SOM dynamics is re-established (Sá et al., 2012). The other often missing aspect to the full implementation of the CA practice is the rotation of diverse crop types, inter-cropping, or other green manuring practices. It remains unclear to what extent countries reporting CA area to FAO may rather refer to ~~this~~ partial adopted practice of CA, i.e. no-tillage only. Applying ~~T~~the presented tillage system dataset in global assessment is a major step forward compared to globally rather homogeneous assumptions on tillage systems (Hirsch et al., 2017; Levis et al., 2014) or a total ignorance of soil management practices (Folberth et al., 2016; Rosenzweig et al., 2014). The rule-based approach and the publication of the underlying data processing scripts allow for extensions of this work, if further relationships can be identified or improved data become available. It also allows for constructing future scenarios, consistent with other scenario frameworks on climate, economic development, and land-use change (e.g. Popp et al. (2017)). Further research is needed to generate global land management datasets with high resolution on crop rotations, residue management, and multiple cropping, so that the full set of CA principles can be simulated and biophysically assessed in comparison to further sustainable land practices.

5 Data availability

~~The presented tillage system dataset and source code are accessible via an open-data repository for modeling communities interested in the quantitative assessment of biophysical and biogeochemical impacts of land use and soil management. The tillage dataset can be downloaded from: http://doi.org/10.5880/PIK.2018.012 and the corresponding R-code from: http://doi.org/10.5880/PIK.2018.013.~~ The presented tillage system dataset and source code are available under the ODBL (data) and MIT (source code) licenses. The tillage dataset can be downloaded from: http://doi.org/10.5880/PIK.2019.009 and the corresponding R-code from: http://doi.org/10.5880/PIK.2019.010. The dataset is provided in netCDF format (version 4) and consists of 42 layers each reporting crop-specific tillage systems per grid cell. Additionally, we provide a layer ~~with~~ indicating area, where adoption of Conservation Agriculture could be facilitated (scenario CA area). The dataset can be used as a direct input, be applied as a mask or overlay for identifying tillage area. The R-code is provided to increase transparency of our methods but also to enable other modelling groups to adjust our tillage area mapping algorithm to their needs, e.g. for different input data or scenarios.

Supplementary information (SI) is available in the online version of this article.

Author contributions

V. Porwollik, C. Müller, S. Rolinski, and J. Heinke developed the tillage system dataset. V.P. collected the input data and wrote the scripts for processing and analyzing the data. C.M and J.H. suggested the CA area downscaling procedure whereas J.H. proposed the application of logit model. V.P. prepared the manuscript with contributions from all co-authors with respect to interpretation of the results and writing of the final paper.

Competing interests

The authors declare that they have no conflict of interest.

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Table 1 Six tillage systems and suggested parametrization for model applications (note that: a) several values per tillage system refer to each single tillage event within each tillage system in the same order as mentioned under the frequency per year, and b) for reduced tillage the inversion and mixing efficiency is depending on the specific form of practice ~~reduced tillage~~ as mentioned above).

Tillage system	**Conventional annual tillage**	**Rotational tillage**	**Conservation Agriculture**	**Traditional annual tillage**	**Traditional rotational tillage**	**Reduced tillage**
Soil management components	Tillage for seedbed preparation, cultivation, post-harvest tillage	Tillage for seedbed preparation, cultivation, post-harvest tillage	Minimum mechanical soil disturbance with direct seeding	Hoe or cutlass for seedbed preparation, cultivation, post-harvest tillage	Hoe or cutlass for seedbed preparation, cultivation, post-harvest tillage	Tillage for seedbed preparation, cultivation, post-harvest tillage
Soil layer inversion ~~per tillage operation~~	Yes, no, yes	Yes, no, yes	No	Yes, no, yes	Yes, no, yes	(Yes), no, (yes)
Frequency and timing per year	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establishment), 1 after harvest	1 before seeding, ~~annually~~ 1 to 2 cultivation, 1 after removal	1 at seeding	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establishment), 1 after harvest	1 before seeding, ~~annually~~ 1 to 2 cultivation, 1 after removal	1 before seeding, 1 to 2 cultivation (10 days to 2 weeks after establish-ment), 1 after harvest
Depth (cm)	20, 5, 20	20, 5, 20	5	10, 5, 10	10, 5, 10	<20~~15~~, 5, <20~~15~~
Mixing efficiency (%)	90, 20, 90	90, 20, 90	5	50, 20, 50	50, 20, 50	90, 20, 90
Soil surface affected (%)	100, 33, 100	100, 33, 100	20 to ~~–~~ 25	100, 33, 100	100, 33, 100	100, 33, 100
Soil surface covered by residues after ~~seedbed preparation~~planting (%)	<15	<15	>30	<15	<15	15–30

Table 2 Gridded and national scale datasets used for mapping tillage.

Global gridded dataset	Resolution (~~degree~~arc-minutes)	Temporal coverage (year)	Source
Crop-specific cropland	~~0.083°~~5	2005	SPAM2005:~~-~~ IFPRI/IIASA (2017b)
Soil depth to bedrock	~~0.1°~~6	1990-2014	SoilGrids: Hengl et al. (2014)
Field size	~~0.0083°~~0.5	2005	Fritz et al. (2015)
Water erosion	~~0.083°~~5	1990-2011 (~2000)	GLADIS: Nachtergaele et al. (2011)
Aridity	~~0.16667°~~10	1961-1990	FAO (2015)
National data			
Conservation Agriculture (CA) area	country	2002-2013	FAO (2016)
Income level	country	2005	World Bank (2017)

Table 3 Correlation coefficients (r) according to 'Pearson' between spatial predictor variables (crop mix, field size, erosion, and aridity) across all grid cells containing potential CA cropland globally.

(r)	Field size	Erosion	Aridity
Crop mix	0.322	-0.104	-0.241
Field size		-0.356	-0.141
Erosion			-0.002

Table 4 Global aggregated tillage system areas and shares on total cropland (IFPRI/IIASA, 2017b).

Tillage system	Tillage system area sum (km^2)	Share of tillage system area on total cropland (%)
Conventional annual tillage	4,650,498	41.10
Traditional annual tillage	4,015,279	35.49
Conservation Agriculture	1,101,899	9.74
Rotational tillage	741,798	6.56
Traditional rotational tillage	650,509	5.75
Reduced tillage	154,403	1.36
World	**11,314,386**	**100**

~~**Table 3** Correlation coefficients (r) according to 'Pearson' between spatial predictor variables (crop mix, field size, erosion, and aridity) across all grid cells containing CA-suitable cropland globally.~~

~~**(r)**~~	~~**Field size**~~	~~**Erosion**~~	~~**Aridity**~~
~~**Crop mix**~~	~~0.322~~	~~-0.104~~	~~-0.241~~
~~**Field size**~~		~~-0.356~~	~~-0.141~~
~~**Erosion**~~			~~-0.002~~

Table 5~~4~~ Logit model input parameters, as midpoint (*xmid*) and slope (*k)* of the four logit model input datasets (columns 1 and 2), which are altered per sensitivity setting. Correlation coefficients (*r*) for ranks according to 'Spearman' between the reference case (Logit-ref) and the perturbed slope and variable combinations of the logit model ~~version~~ results are given, illustrating the sensitivity of the grid cell likelihood ~~to have~~of potential CA~~-suitable~~ area (columns 3 to 6).

Variable	Logit-ref (xmid)	Logit-ref (k)	Logit-ref/ and k+100 % (r)	Logit-ref/ and k-50 % (r)	Logit-ref/ and drop one variable (r)	Logit-ref/ and one~~-~~ variable only (r)
Field size	20	0.25~~0~~	0.975	0.988	0.944	0.555
Erosion	12	0.017	0.992	0.997	0.989	-0.119
Aridity	0.65~~0~~	-5	0.966	0.982	0.901	0.607
Crop mix	0.50~~0~~	10	0.981	0.971	0.773	0.826

Table 6~~5~~ Global sums over 22 CA -suitable crop type areas ~~(ha)~~, sorted decreasing shares of downscaled CA area values on the identified potential CA~~-suitable~~ area ~~(%)~~, and crop-specific downscaled CA areas ~~(ha)~~.

Crop type	~~Area suitable for~~Potential CA area (km^2~~ha~~)	Share of downscaled on potential ~~area suitable for~~ CA (%)	Downscaled CA area ~~area~~ (km^2~~ha~~)
Soybean	740,797~~74,085,533~~	48	359,205~~35,922,509~~
Wheat	1,341,590~~134,155,907~~	24	321,305~~32,123,029~~
Maize	762,415~~76,236,593~~	19	143,432~~14,345,219~~
Barley	485,428~~48,540,127~~	12	57,959~~5,798,762~~
Rapeseed	144,601~~14,463,189~~	31	45,363~~4,536,453~~
Sunflower	186,310~~18,626,706~~	20	36,716~~3,672,963~~
Sorghum	97,918~~9,784,525~~	24	23,816~~2,380,535~~
Bean	119,902~~11,986,897~~	20	23,535~~2,355,186~~
Other cereals	231,384~~23,138,040~~	10	22,109~~2,211,589~~
Cotton	84,069~~8,408,017~~	25	21,121~~2,112,172~~
Other pulses	76,869~~7,685,206~~	21	15,932~~1,595,015~~
Lentils	19,015~~1,901,924~~	45	8,565~~856,723~~
Pearl millet	56,062~~5,601,798~~	11	5,938~~588,589~~
Rest	82,063~~8,208,157~~	5	4,081~~407,596~~
Groundnut	47,208~~4,722,927~~	7	3,308~~330,506~~
Chic-pea	28,489~~2,847,020~~	11	3,227~~322,613~~

Crop type	~~Area suitable for~~Potential CA area (km²~~ha~~)	Share of downscaled on potential ~~area suitable for~~ CA (%)	Downscaled CA area ~~area~~ (km²~~ha~~)
Small millet	13,419~~1,341,620~~	21	2,859~~286,056~~
Vegetables	90,535~~9,053,627~~	2	1,834~~183,537~~
Tobacco	13,678~~1,367,825~~	7	916~~91,765~~
Sesame~~-~~seed	17,940~~1,795,517~~	3	502~~49,984~~
Pigeon~~-~~pea	6,411~~638,036~~	2	129~~15,150~~
Cowpea	6,317~~632,054~~	1	48~~4,812~~
World	**4,652,419~~465,221,244~~**	**24**	**1,101,899~~110,190,763~~**

~~**Table 6** Global aggregated cropland(IFPRI/IIASA, 2017b) area (ha) and share (%) per tillage system~~

~~Tillage system~~	~~Sum over cropland and grid cells (ha)~~	~~Share of tillage system area on total SPAM2005 cropland (%)~~
~~**Rotational tillage**~~	~~74,218,834~~	~~6.56~~
~~**Traditional rotational tillage**~~	~~65,044,354~~	~~5.75~~
~~**Traditional annual tillage**~~	~~401,538,934~~	~~35.49~~
~~**Conservation Agriculture**~~	~~110,190,763~~	~~9.74~~
~~**Conventional annual tillage**~~	~~465,037,862~~	~~41.10~~
~~**Reduced tillage**~~	~~15,407,865~~	~~1.36~~
~~**World**~~	~~**1,131,438,612**~~	~~**100**~~

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Table 7 ~~Derived~~ T~~t~~illage system area results compared to estimates of Erb et al. (2016) on tillage intensity areas. The first two columns show our aggregated tillage system area values, columns three and four additionally include the young and temporal fallow cropland area by Siebert et al. (2010), a cropland area not represented in SPAM2005 and therefore added to our total cropland as well as to the 'low intensity' category as described in Erb et al. (2016). Note that Siebert et al. (2010) state, that about 4.4 ~~0,000,000~~ Mkm^2~~ha~~ of cropland were young and temporal fallow (< 5 years) around the year 2000.

Tillage system ~~group~~	**Tillage area this study (km^2~~ha~~)**	**Tillage area this study (%)**	**Tillage area this study + fallow (km^2~~ha~~)**	**Tillage area this study + fallow (%)**	**Tillage area (km^2~~ha~~) (Erb et al., 2016)**	**Tillage ~~area~~ share (%) (Erb et al., 2016)**
Low intensity	2,648,610~~264,861,816~~	23.4~~23.4~~	7,048,610~~704,861,816~~	44.9~~44.9~~	4,730,000~~473,000,000~~	38.9~~38.9~~
High intensity	8,665,776~~866,576,796~~	76.6~~76.6~~	8,665,776~~866,576,796~~	55.1~~55.1~~	7,430,000~~743,000,000~~	61.1~~61.1~~
World	**11,314,386~~1,131,438,612~~**	**100**	**15,714,386~~1,571,438,612~~**	**100**	**12,160,000~~1,216,000,000~~**	**100**