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Nearly half of the world is suitable for diversified farming for sustainable intensification

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Sustainable intensification, defined as increasing production per unit without harming the environment, has potential to transform agricultural systems. While questions persist about which practices and conditions lead to sustainable intensification, diversification has gained prominence as a proposed solution. Here we apply niche modelling using maximum entropy modelling approach to predict the global spatial distribution of profitable diversified farming systems under different socio-economic conditions. We found about 47% of the world is suitable for profitable diversified systems with a larger area in the global North. When we combined our findings with knowledge about biophysical potential for cropland expansion and intensification, we found that different areas could benefit from diversification to achieve sustainable intensification through cropland expansion (e.g., Europe), intensification (e.g., sub-tropics and tropics), or both (e.g., West Africa). With these results, we provide insights in which way diversification can support sustainable intensification and contribute to the debate on land sharing vs sparing.

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Current agricultural systems are not well designed to meet food demands and conserve biodiversity at the same time. While predominant agricultural practices are often vulnerable to multiple risks, including climate change and market shocks, they are also drivers of land degradation[1], biodiversity loss[2,3], poor household diets[4] greenhouse gas emissions[5], and limited long term sustainability[6]. As the demand for agricultural commodities is expected to increase tremendously (35–56% between 2010–2050)[7], pressure is increasing to either further intensify farming systems or to expand cropland. While these events might increase food production, they will also lead to further biodiversity loss and higher vulnerability of poor and marginalized communities[5].

The abundance of scientific evidence pointing out the unsustainability of agricultural practices has led to a growing demand for a system transformation of agriculture by policy makers, NGOs, and governmental bodies. However, the exact nature and structure of this transformation remains a subject of highly controversial debates. It has been argued that agricultural intensification can increase food production thereby limiting the need to increase agricultural area. At the same time, agricultural intensification might lead to reduced levels of biodiversity on the field e.g., due to heavy use of pesticides. Agricultural extensification might improve biodiversity by providing suitable conditions and space for diverse habitats and ecosystems, which in turn can attract a wider range of plant and animal species. At the same time, extensification may also trigger additional deforestation and biodiversity loss through agricultural expansion. In the conservation community, this dilemma has been discussed in the context of the land sharing vs. land sparing debate, with one side arguing for further intensification to save as much land as possible from conversion to agricultural land and the other side supporting extensification to conserve on-farm biodiversity[8–10]. However, intensification is faced by criticism and concerns of whether spared land is put under conservation[11] and extensification might not be as beneficial to farm biodiversity conservation if it contributes to deforestation[12] or mainly benefits generalists[13]. Other scholars have argued that there is an optimal window of sustainable intensification (SI), where tradeoffs between both approaches are minimized[14]. Yet, although many different approaches for SI have been suggested, it remains unclear how agricultural practices would have to change under a system of SI and how this would depend on local context variables. In some areas SI most likely would require extensification as agricultural practices are already highly intensified to a degree which can be considered unsustainable while in other regions SI would require intensification as the major sustainability challenge is increasing natural habitat conversion[15,16]. As such, SI is not homogenous but rather highly context specific. In this study we borrow the definition by van Grinsven et al.[10]. on "sustainable intensification as increasing food production per unit hectare without compromising the environment and degrading natural resources and sustainable extensification as decreasing the depletion of natural resources and environmental impacts while limiting the decrease of food production per unit hectare".

In this study we argue that diversified farming systems (DFS) are a key element of SI as they can support both intensification as well as extensification, in different contexts and under different socioeconomic conditions. They have the potential to improve ecosystem services, processes, and functions[17], including pest and disease control, water quality regulation and mitigation of ground water depletion by up to 19%, weed control, soil health improvement by increasing soil carbon content, pollination, and carbon sequestration and mitigation[18–24]. At the same time, increasing diversity on farms has also been found to provide co-benefits in yield, yield quality and system resilience and stability as in accordance with ecological theory[9,25,26].

Management practices in diversified farming systems including crop rotation, agroforestry, inter cropping, embedding natural habitats (e.g., vegetation strips, hedgerows), and mixed crop and livestock farming can be used to shift farming systems towards a state of SI. In extensively managed systems, often characterized by low input agrochemicals, and high diversity croplands with low yields, crop production could be intensified through rotating mixed crops, increasing cropping density in mixed plantings, vegetation strips or through agroforestry systems. Intensively managed systems on the other hand, often signified by large tracts of monocultures managed with high agrochemicals[27–29], could be diversified through mixed plantings, agroforestry systems including diversified home gardens[30], boundary planting that involves use of hedgerows or tree breaks[31,32], embedding natural habitats e.g., vegetation strips[33], and diversifying landscapes surrounding croplands[9].

In theory and in practice, there is increasing context dependent evidence about the benefits of DFS on food production by over 10%[18,34], above 20% change in economic output[35,36], reduce ground water depletion by 19%[23,37], carbon mitigation by 11%[38], and biodiversity conservation by over 20%[18–20,34,35,38–40]. Yet, DFS has also been criticized for producing lower yields and profits in comparison to simplified farming systems[35,41] even though the yields are often of high quality and fetch higher prices in stratified markets[42]. This profitability, however, seems to be highly variable and little is known under which circumstances diversification is likely to improve profitability. Furthermore, it is unclear if DFS might trigger a shift towards extensification or intensification in order to reach SI. Although studies have shown cropland suitability distribution combining information on climate, edaphic, and crop specific requirements at different spatial scales[43,44], little is known about the suitability of diversified farming systems and their profitability for farmers influenced by factors such as access to markets and infrastructure[39].

As there is evidence that farmers and other practitioners of agriculture (e.g., funders, donors) are making land use decisions based on the expected profitability[45,46], we predicted suitable locations for profitable DFS globally based on maximum entropy distribution modeling (MaxEnt). Although, this methodology was originally developed for predicting species distributions based on species presence data and in combination with environmental predictors, we apply the method based on locations of profitable DFS in combination with socio-economic predictors. We use the term prediction in this study to refer to evaluation of grid-by-grid suitability based on a set of socio-economic constraints and identification of other areas with similar conditions. With our results, we contribute to the knowledge about factors influencing the distribution of the suitability of DFS, which is crucial for effective policies supporting diversified farming and agricultural system transformation. Moreover, we discuss the concept of diversification as a means to sustainable intensification in the context of land sharing and land sparing debate.

We found that suitable land for profitable diversification ranged from 29 to 93 million km^2 and locations in the global north are highly suitable and only areas in the global south with proximity to major towns/cities are profitable. About 20% (29 km^2) of the world has the highest suitability for profitable diversified farming systems and about 53% is not suitable. When we combined the map about the spatial distribution of profitable DFS sites with knowledge about the biophysical for expansion and intensification potential, to highlight areas that could benefit from DFS as a means of achieving SI, we found that areas in South America and Sub-Sahara are suitable for both profitable

DFS and intensification, while in North America and Europe those areas were suitable for extensification.

Results

Model parameters and evaluation. From the initial 155 models we ran with different settings (combined 8 variables, 5 regularization multipliers and 31 feature class combinations), only one model satisfied all selection requirements except the omission rate, which was slightly above the acceptable level (Supplementary Table 4). Nevertheless, the model was comprised of simple feature classes (lq) and had a good predictive ability (AUC = 0.878). A rerun of the model using only the 5 most relevant predictors (31 feature classes and 5 regularization multipliers) led to a reduced omission rate of 0 and satisfied all selection criteria (Supplementary Table 4). Model features included classes of linear, quadratic, product, and hinge (lqpt).

Habitat suitability under current socio-economic conditions. We found high suitability of profitable DFS across the globe with higher coverage in North America, Europe, and South and East Asia. High suitability in the Global South was in particular around cities and along the coastline. This was also the case, when we applied different thresholds (Supplementary Table 5, Supplementary Fig. 6) to the aggregated suitability map (Fig. 1). In terms of size, when we applied different thresholds (supplementary Fig. 6), we found that suitable areas ranged from 29 to 93 million km^2 (Supplementary Table 6) with the highest share taking balanced training omission rate as a threshold value for, predicted suitable area. When we combined the thresholds (Fig. 1), we found that areas with high suitability accounted for 19.56% (Supplementary Table 7).

Socio-economic variable importance and their impact. Accessibility indicated by the distance to the nearest city, urban center, and market and cropland availability were the two most important variables driving profitability of DFS (Supplementary Table 8).Overall, we found that infrastructural variables (e.g., accessibility, electricity coverage, cell tower distance) together with land allocated for cultivation play a key role in the profitability of diversified farming systems. GDP per capita was not as relevant for the distribution for profitable diversified farming systems (4.8, 9.5).

We predicted higher suitability for profitable DFS in areas with higher accessibility, closer to the urban centers, high electricity coverage (nighttime lights over 60 nW cm^{-2} sr^{-1}, and higher values for governance and accountability (Supplementary Figs. 7 and 8). We found high and increasing probability in areas with 30–60% of land being allocated to agriculture. Higher levels of agricultural area than 60% led to a small decrease in suitability. While we found that accountability, transparency, and openness of government measured by the index on voice was positively correlated with the suitability of profitable DFS, GDP per capita was negatively correlated. Above USD 60,000 of GDP per capita, the probability of suitability for profitable diversified farming systems was <60%.

Suitable areas for extensification and intensification. Areas with high levels of profitable DFS suitability and biophysical potential for cropland intensification can be found in sub-Saharan Africa, along the east coast of Brazil, parts of India and Tajikistan, Australia, and Canada (Fig. 2). At the same time, we found, high suitability of DFS coinciding with high cropland expansion potential in western Europe, India, China, and some parts of Brazil and eastern Europe (Fig. 3). Regions with pockets of land that is suitable for intensification and cropland expansion while also being suitable for high DFS probability include West Africa near the coast of Atlantic Ocean and parts stretching from eastern Africa to southern Africa.

Discussion

We predicted the potential suitable habitat for profitable DFS using a set of socio-economic variables and known occurrences of profitable DFS. To our knowledge, no study has attempted to investigate spatial distribution of profitable DFS at either country, continent, or global levels nor integrated knowledge about suitability for diversification with potential for intensification and cropland expansion.

There is an increasing need for sustainable agricultural production that can satisfy the global demand for food, feed and other agricultural products. Based on our analysis, we found that

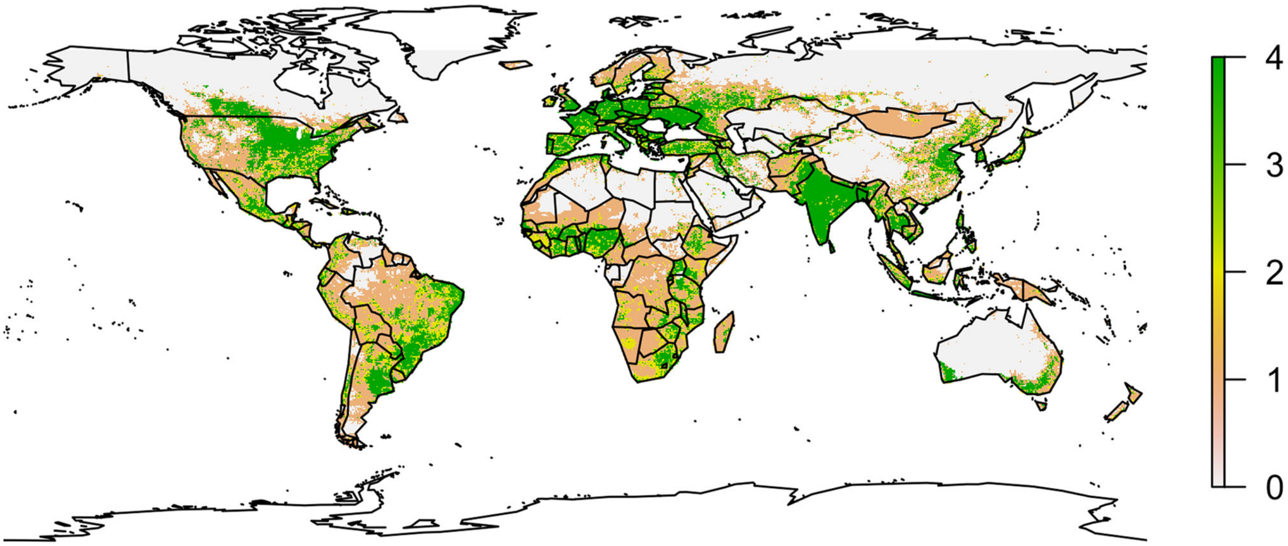

Fig. 1 Suitability of profitable diversified farming systems. Number of models predicting high suitability of profitable diversified farming systems based on four different thresholds to distinguish high from low suitability including balanced training omission, maximum sensitivity plus specificity, equal training sensitivity and specificity and 10 percentile training presence thresholds. Models included 5 predictors variables, which were selected based on their permutation importance (Supplementary Table 8).

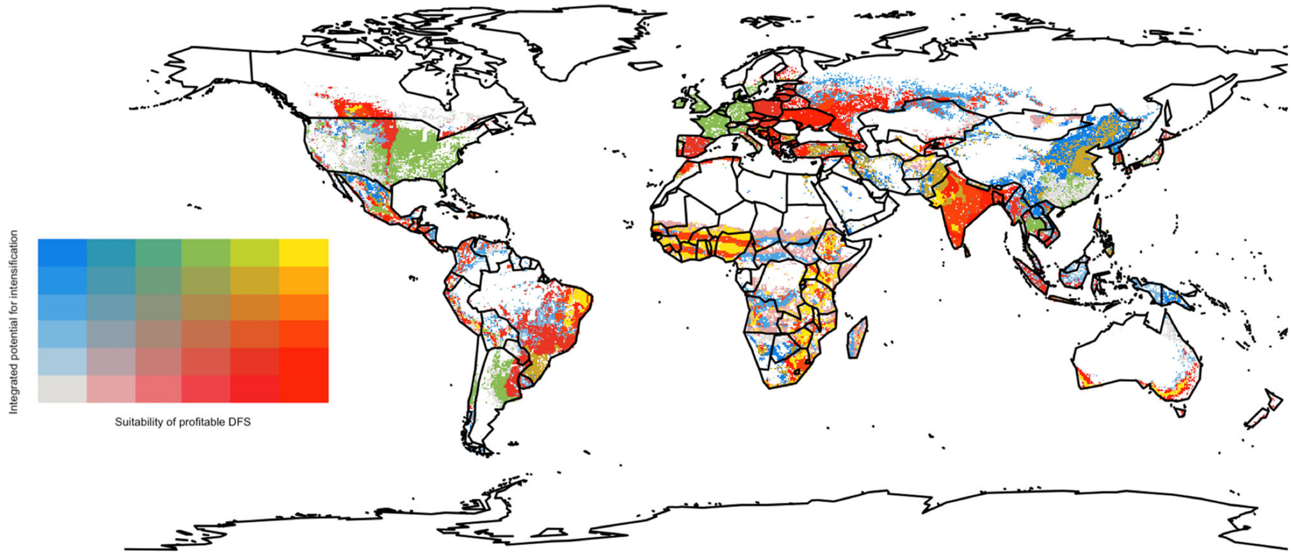

Fig. 2 Suitable areas for intensification of profitable diversified farming systems. Bivariate map of integrated potential for intensification and profitability of diversified farming systems. Yellow indicates high potential for both profitable diversification and potential for intensification while gray indicates less of both. Blue indicates high potential for intensification and low suitability for profitable diversification while red, indicates high suitability for profitable diversification and low potential for intensification.

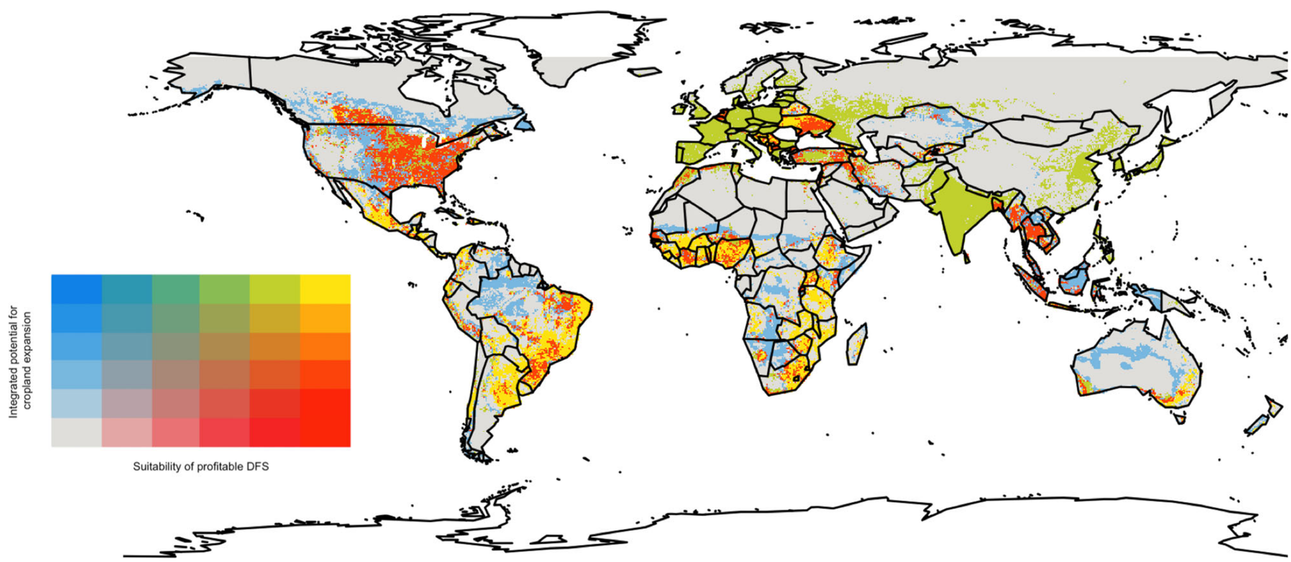

Fig. 3 Suitable areas for cropland expansion and profitable diversified farming systems. Bivariate map of integrated potential for cropland expansion and suitability of profitable diversified farming systems. Yellow indicates high potential for both profitable diversification and potential for cropland expansion while gray indicates less of both. Blue indicates high potential for cropland expansion and low suitability for profitable diversification while red, indicates high suitability for profitable diversification and low potential for cropland expansion.

under current conditions the Global North is by tendency more suitable for profitable DFS compared to the Global South due to a well-developed infrastructure and established markets, offering premium prices for products from DFS e.g., with certificates like "sustainable" or "organic"[47]. In the Global South, we found that high suitability was by tendency higher within proximity to major cities supporting our assumption about the relevance of infrastructure for DFS profitability i.e., road connectivity, ICT, and electricity coverage to profitability. In addition, studies like Kumar et al.[48], found that farmers are more likely to adopt new farming technologies when they are in proximity to urban centers or markets. Weis et al.[49] found that over 50% of the population in countries in sub-Saharan Africa live over one hour away from the city. Low infrastructure development in many countries in the Global South with limited ICT, and electricity coverage (~46% of the population was served by 2020[50]) contributes to high costs of doing business, limited shelf life of produce and a lack of value addition[51].

Our results are in line with these studies supporting the relevance of infrastructure for agricultural profitability, which has been found to be highly relevant by other studies. In line with other studies like Irungu et al.[52] in Kenya, Jolex and Tufa[53] in Malawi, we found that profitability of the agri-prenuers increased with the number of access to ICT tools. Similarly, our results indicate an important role of electricity coverage and market access in line with findings of other scholars[51,54,55], who also support the relevancy of these variables for the profitability of farming systems, which are highly dependent on access to markets. In our study, voice and accountability increased suitability for profitable DFS. Some studies using the voice and transparency variable found a similar positive relationship between economic growth and governance in the Global North[56], while others found a negative correlation between voice and transparency and economic growth, e.g.[57] in East Asia and Pacific regions. However, the latter study by Samarasinghe 2018[57] also found that control of corruption can result in an approximate positive change of up to 7% to economic growth. While other governance indicators like political stability, regulatory effectiveness, control of corruption, and governance effectiveness are likely to play an important role in economic growth and the profitability of diversified farming systems, we included only voice and accountability, as it was highly correlated to other variables. Overall, based on our findings we would argue that governance is important for profitable agriculture and most likely even more for diversified farming systems.

The differing results for the Global North and South suggest that different strategies are likely to be necessary for the support of DFS and sustainable intensification. For example, suitability in the Global North could be leveraged to increase extensification processes in many farms, which are currently heavily intensified. In the Global South, on the other hand, effective policies for DFS would require efforts to increase the suitability of agricultural areas such as the development of new markets and transport routes of DFS products. As these measures might also trigger other negative feedback loops in terms of land use change, increasing land use prices, and opportunity costs for conservation, it should be carefully considered whether intensification actually compensates for these tradeoffs.

In this study we modeled profitability of DFS based on socioeconomic variables not considering other relevant factors including bioclimatic variables, land cover, crop choice and crop combination or adoption rates. Despite the relevance of these variables, we decided not to include them for different reasons. First of all, bioclimatic variables are crop specific and presence data used in this study considered a wide range of crop combinations as DFS. As different crops have different specific biophysical requirements, even though most of the major crops' requirements overlap, predicting the suitability of profitable DFS on a global scale would require separate models for different crop choices and combinations. Moreover, we combined our prediction with knowledge about the biophysical potential for cropland expansion and intensification thereby indirectly considering bioclimatic and land cover variables and their relevance for agricultural productivity. Specifically, the maps included crop requirements from FAO land evaluation hence spatially restricting regions that are suitable[58]. In Zabel et al.[59]. the authors noted that land available for conversion was based on land cover classification and ultimately excluded classifications e.g., urbanized land that would not be available for conversion. Additionally, diversification may improve climate resilience outcomes through higher yields and improved yield stability compared to simplified farming systems[60]; Furthermore, diversification is likely to reduce emissions from farmland through soil organic carbon storage[61], the restoration of soil nutrients, atmospheric nitrogen fixation and improved availability of these nutrients to plants leading in turn to reduced leaching and mineralization losses[9,37].

We found most areas with high DFS profitability in combination with high potential for intensification in Sub-Sahara Africa and South America. However, projection of crop expansion (10–25%) by 2050 are also mostly expected in these regions[62], threatening some of the most biodiverse areas in the world[63,64]. In addition to this, these areas are often characterized by extensive production systems. Sustainable intensification on existing agricultural land could contribute to bridging the gap between current yields and production potential without converting additional natural habitats to agricultural land. This could be achieved for example through a better management of nutrients and water, which we find in many DFS including agroforestry, mixed planting on crop rotations, or combining livestock and crop production.

We found most areas with the highest cropland expansion potential while also having high suitability for profitable diversified farming mainly in Europe. Most agricultural areas in Europe are highly intensified in terms of nutrients, pesticides, and water use[65]. Intensification levels in many of these areas have led to a situation where agriculture is one of the key drivers of groundwater and surface water depletion and pollution[66]. Biodiversity conservation in Europe is mainly in protected areas that are generally large in numbers (accounting for ~26% of the EU land according to the EU Biodiversity strategy) but are rather small in size[67]. Conservation in the agricultural landscapes is still limited in within the member states of European union[68]. To achieve the 30% EU biodiversity strategy target it might be necessary to expand protected areas into agricultural lands and promoting agricultural extensification. Beyond increasing cropland areas, other forms of extensifying agricultural production like mixed plantings, incorporating natural habitats e.g., vegetation and grass strips and hedgerows, and reducing the cropping density (e.g., number of harvests per year)[37] would play an important role in reaching SI levels. Cropland expansion might present a challenge due to the high demand for land for other uses including settlements, industries, and biodiversity conservation.

In line with Zabel et al.[64]. we found that areas suitable for cropland expansion are also often areas rich in biodiversity. Land use demand for cropland, in particular within these areas are likely to create conflicts. It would be extremely important to carefully balance these different needs on a smaller scale to assure additional land taken into production are not important biodiversity sites while maintaining high levels of on-farm biodiversity. A general reduction of demand for agricultural non-food products, e.g., for fodder or bioenergy, would be a key measure to generally reduce increasing pressure on and demand for agricultural land[12]. We would argue that a shift to more sustainable levels of intensification and increased levels of biodiversity on agricultural land without an unacceptable loss of yields or biodiversity can be achieved through a simultaneous introduction of DFS and, where possible, a significantly reduced demand for agricultural land.

Like other modeling approaches estimating suitability in particular of DFS profitability are prone to uncertainties due to input data quality, complex system interactions and simplified assumptions. We also caution readers that issues of scale play a significant role in predicting DFS profitability and the results validity[69]. As we had to compromise between the availability and accuracy of data, we integrated data from different years and different original resolutions. As the results of our study depend on different variables used as predictors and, in the case of Zabel et al.[59] to combine with our DFS suitability map, we have to acknowledge that compounding uncertainty from multiple sources is likely to impact our results for example in the case of China. To overcome these uncertainties, we applied strict statistical measures to confirm the robustness of our models and as suggested by other authors, captured levels of uncertainty by applying different thresholds to distinguish suitable from non-suitable areas for DFS rather than a single fixed value[70].

Regardless of these uncertainties we emphasize that our findings are relevant for farmers, investors, land use planners and decision-makers aiming to utilize the potential of DFS for sustainable intensification. Many studies have found that both food production and conservation of biodiversity can be achieved concurrently by utilizing methods like diversification[9,17,19,34]. With this study we contribute to a better understanding of the conditions defining profitability of DFS and identify areas where diversification might be a viable option to simplified farming systems supporting SI in different ways. These findings are relevant for decision making, especially of farmers, agricultural investors, and land use planners, interested in investing, supporting, or adopting DFS. We conclude that DFS to achieve SI purges the framing of either-or of land sharing and sparing, reframing the narrative of agricultural transformation[14].

Methods

Data collection

Occurrence data. Data on profitability of DFS were obtained from a meta-analysis by Sánchez et al. (2022)[36,71]. This meta-analysis summarized scientific findings about the profitability of DFS and simplified farming systems based on 119 peer-reviewed publications yielding 3192 comparisons of intervention versus control practices. Diversified farming practices included in the meta-analysis were crop rotation, intercropping, associated plants, combined practices, agroforestry and embedded natural systems while simplified farming practices included monoculture, and practices that when compared with diversified practices had comparatively lower number of varieties or species e.g., a crop rotation with a single crop compared with crop rotation in tandem with intercropping or with multiple crops, or simple agroforestry with a single tree species compared to a multi-strata agroforestry[36]. Effect sizes based on the comparisons of profitability of diversified and simplified farming practices were summarized in the dataset by information on the study location and experiment design including treatment, methods, and measured indicators. Effect sizes were calculated as log response ratios for gross income, total costs, and benefit cost ratio and Standard Mean Difference (SDM) for gross margin and net incomes (Supplementary Table 1).

We classified all positive effect sizes as profitable and negative as unprofitable DFS. We used presence locations of profitable DFS to model DFS suitability and excluded duplicated presence locations (some comparisons were from the same study area). We combined the remaining 114 presence and 93 absence records, with different predictor variables to model suitability of profitable DFS (Supplementary Fig. 1).

Predictor variables. Different variables influence profitability of diversified farming practices at different scales including farm, country, region, and global scale. In this study, we use 14 variables (Supplementary Table 2), to predict the suitability of profitable DFS, which we selected based on past published literature (See Supplementary Note 1). These variables included environmental (cropland area and soil organic carbon), social (population size and density), economic (electricity coverage, time taken to travel to nearest urban center, and Information and Communication Technology (ICT) coverage, human development index, and Gross Domestic Product), and political and governance factors (voice and accountability, rule of law, absence of political violence, government effectiveness, and regulatory quality). We rasterized and resampled all data to a spatial resolution of 2.5 arc minutes, the same projection, and the same geographic extent.

We excluded highly correlated variables (Pearson correlation coefficients >0.8), which have been shown to affect the quality of the models and increase uncertainties in prediction[72], and used eight uncorrelated variables for modeling purposes (Supplementary Table 3, Supplementary Fig. 2).

Modeling approach. We used a maximum entropy (MaxEnt) modeling approach to assess the spatial distribution of socio-economic suitability for profitable DFS. MaxEnt belongs to the family of machine learning approaches and builds models by evaluating the suitability of each grid cell to predict the species occurrence potential or probability as a function of a set constraints[73]. MaxEnt has been applied mainly to predict species richness, spread of invasive species, hotspots for endemism and impacts of climate change on species distribution[74] but increasingly, it is also used for other purposes e.g., to predict the distribution of fishing activities[75], renewable energy sites[76], and cultural ecosystems[77].

MaxEnt models suitability based on presence records (e.g., coordinates of profitable DFS) and a set of spatially explicit data representing constraints in the form of environmental or socioeconomic variables. Unlike other distribution models, which often require presence and absence records, MaxEnt is a presence only model. While our original data on profitability included absence records (those locations where diversified farming was not profitable under certain conditions), we did not consider them as true absences. This is because many studies included metadata analysis by Sánchez et al.[36]. found that profitability differed with crop choice and farm management conditions indicating that DFS might be profitable after all in the same locations under different assumptions.

Model creation, calibration, and evaluation. We used the kuenm package[78] in R[79] to develop, calibrate and select the best performing MaxEnt model. To this end, we created 155 candidate models through a combination of 8 variables, 5 regularization multipliers (0.5, 1, 2, 3, and 4) and 31 combinations of all feature classes (linear, quadratic, product, threshold, and hinge). Selection of the best model was based on 3 requirements, i.e., 1) statistical significance evaluated based on partial Receiver Operating Characteristic (ROC) with 500 iterations and 50 % of the data for bootstrapping, 2) predictive power indicated by the omission rate and an omission error rate ≤ 5%, and 3) model complexity calculated as maximum delta Akaike Information Criterion (AIC) ≤ 2. Models that met these criteria were remodeled using ten-fold cross validation. Based on the Area Under the Curve (AUC), we evaluated the models' goodness of fit.

We selected the model with the least omission rate to create binary (presence/absence) maps. Where omission rates of two models were the same, we chose the one with the least delta AIC, and if delta AIC was the same, we selected the model with the least feature classes (simple model). We used 4 suitability thresholds to create binary maps i.e., maximum training sensitivity plus specificity (mtss), balanced training omission (bto), equal training sensitivity and specificity (etss), and 10 percentile training presence (ptp). Through the selection of multiple thresholds and their comparisons we were able to account for uncertainties inherent to modeling approaches with imperfect data.

We used MaxEnt output format cloglog (complementary log-log transformation), which ranges from 0 to 1 and argued to be a better predictor of the probability of presence than the logarithmic transformation commonly used before the cloglog option[80]. Based on jackknife results of the initial model, we selected predictor variables (Supplementary Fig. 3) using the top 5 predictor variables of the permutation importance estimate. These variables were accessibility, cropland area, voice and accountability, nighttime lights, and GDP per capita (Table 2). Model development, calibration, evaluation, and creation of binary suitability maps were performed using the same procedure, regularization multipliers and feature classes as the initial model.

Towards sustainable intensification. Data on the integrated potential for cropland expansion and intensification were obtained from Zabel et al.[59], who examined tradeoffs between agricultural impacts brought about by cropland expansion and intensification in the future and biodiversity. The authors in Zabel et al.[59] combined information on biophysical with socio-economic conditions expected by 2030. In the case of cropland expansion potential, they included the aggregated biophysical potential of 17 crops and the land theoretically available for expansion. For intensification, the potential was derived based on the potential simulated yield of 17 crops under ideal conditions and validated on field trials. Comparing the potential yield against the statistical yield, the authors assessed the biophysical intensification ratio, which was then combined with marginal profitability of crops. The marginal profitability was predicted by reallocating crops iteratively while changing some dynamics like climate change, change in consumption patterns among others to achieve a stable allocation.

Hence, in this study Zabel et al.[59] data on a) integrated potential for cropland expansion (Supplementary Fig. 4) and b) integrated potential for intensification (Supplementary Fig. 5) were used to show areas where DFS could contribute to either extensification or intensification as a way to achieve SI.

We created bivariate maps combining each of these two maps from Zabel et al.[59] with the suitability map of profitable DFS that we created. These bivariate maps were created on R programming language[79] using package "classInt"[81].

Data availability

Existing and original datasets for data used in this study can be obtained on web. Data on profitable diversified farming systems locations (dataset used for supplementary Fig. 1) and socio-economic variables used in this study can be accessed at https://doi.org/10.60507/FK2/V13Z99.

Code availability

All analysis were done in R (v.4.2.0) with kuenm package for MaxEnt modeling. The R code is available upon request.

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Author contributions
H.K. and L.B.F. elaborated the study design. H.K. and S.R. collected the data. H.K. data curation and analysis, and wrote first draft. H.K. and L.B.F. revised and edited the manuscript. L.B.F. acquired the funds and supervised the work.

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