Impacts of climate change on agro-climatic suitability of major food crops and crop diversification potential in Ghana

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Abstract
Crop diversification is a promising climate change adaptation strategy for food production stability. However, without quantitative assessments of where, with which crop mixes and to what extent diversification is possible now and under future climatic conditions, efforts to expand crop diversification under Nationally Determined Contributions (NDCs) and National Action Plans (NAP) are unsystematic. In this study, we used extreme gradient boosting, a machine learning approach to model the current climatic suitability for maize, sorghum, cassava and groundnut in Ghana using yield data and agronomically important variables. We then used multi-model future climate projections for the 2050s and two greenhouse gas emissions scenarios (RCP 2.6 and RCP 8.5) to predict changes in the suitability range of these crops. We achieved a good model fit in determining suitability classes for all crops (AUC=0.81-0.87). Precipitation-based factors are suggested as most important in determining crop suitability, though the importance is crop-specific. Under projected climatic conditions, optimal suitability areas will decrease for all crops except for groundnuts under RCP8.5 (no change: 0%), with greatest losses for maize (12% under RCP2.6 and 14% under RCP8.5). Under current climatic conditions, 18% of Ghana has optimal suitability for two crops, 2% for three crops with no area having optimal suitability for all the four crops. Under projected climatic conditions, areas with optimal suitability for producing two and three crops will decrease by 12% as areas having moderate and marginal conditions for multiple crops increase. We also found that although diversification opportunities are spatially distinct, cassava and groundnut will be more simultaneously suitable for the south while groundnut and sorghum will be more suitable for the northern parts of Ghana under projected climatic conditions.

Keywords: diversification, agricultural suitability, food crops, climate change, Ghana

1. Introduction
The agricultural sector of tropical countries is at great risk from the impacts of climate change. This is because of changes in weather patterns, which determine yields and crop production in these areas [1, 2].
Agricultural intensification, crop diversification, irrigation, improved crop varieties and other agronomic management strategies are needed to stabilize or enhance food production now and under projected climatic conditions. Of these options, crop diversification requires special attention because it can stabilize national and local food production [3-6], improve dietary choices [7-10], increase on-farm ecosystem services [11-14], avert micro-nutrient deficiencies and improve household health outcomes [7, 15] and increase incomes of smallholder farmers [16-18].

Studies have shown that crop diversity contributes to resilience through a type of “insurance” where a failure in one crop is mitigated by another crop/cultivar and also through more efficient resource partitioning at various scales [5, 19, 20]. As such, crop diversification has been shown to be beneficial to building climate resilience in many countries such as in China [21], Canada [22], Kenya [23], Ethiopia [24], Malawi [9, 18], Zimbabwe [25] and also Ghana, [26, 27]. Crop diversification is achieved through multiple cropping where farmers grow two or more crops in sequence (relay cropping) or together (intercropping and mixed cropping) within the same year. The ability of farmers to diversify is based on the concurrent (for intercropping) or sequential (for relay cropping) biophysical suitability of the crops in their area.

Crop suitability is a measure of the climatic and other biophysical characteristics of an area to sustain a crop production cycle to meet current or expected targets [28, 29]. When combined with climate projections, suitability assessments are used to gauge shifts in crop potential under climate change [30, 31]. Despite massive developments in agricultural production technology, weather and climate still play a significant role in influencing agricultural production in Africa and elsewhere [32-34]. In particular, under rain-fed conditions the production potential of a crop depends on the climatic conditions of an area. Therefore, each crop will thrive within a specific climatic envelope that can be enhanced by management – yet climate change will alter satisfaction of these requirements and subsequently the geography of crop suitability [35].

Despite the potential of crop diversification for improving agricultural production and stability especially under climate change, few studies have focused on design of diverse agricultural systems. There are no explicit indications of which crop combinations work where and with what individual or combined production outcomes. Impact studies have also mostly focused on individual crops with testing of adaptation measures following the same pattern. To the best of our knowledge, there are no publications to inform diversification directions at national or local levels to guide farmers to select most suitable crops for their areas, despite knowledge of the high potential of diversification in building resilience. Consequently, it is very difficult to measure progress or changes towards crop diversification between
different times and locations as response to climatic or systematic policy stimulus [36]. In this regard, diversification potential assessments are imperative for targeted adaptation planning and investment under Nationally Determined Contributions (NDCs) for countries such as Ghana. Furthermore, systematic agricultural diversification interacts with many sustainable development goals (SDGs) such as reduction of poverty (SDG1), averting hunger (SDG2), enhancing good health and well-being (SDG3), responsible consumption and production (SDG12), reducing impacts of climate change (SDG13) and sustenance of life on land (SDG15) [37, 38].

In this study, we applied crop climatic suitability models to assess the impact of climate change on the potential for crop diversification as combined suitability for cassava, groundnuts, sorghum and maize in Ghana. Maize, sorghum, cassava and groundnuts are important staple crops planted on nearly three million hectares annually, which is ~83% of all the cropped area in Ghana [39]. Furthermore, diets in Ghana include combinations of maize or sorghum, cassava and groundnut in various proportions [40, 41], making it important that these crops are available also under climate change. There is a paucity of data on spatially explicit climate change impact assessments and limited analysis of impacts on multiple crops to guide crop diversification as an option for resilience. Therefore, the aim of this study was to assess the impacts of projected climate change on four important food crops in Ghana by mid-century and their ability to be produced together. Specifically, we intended to (i) identify the determinants of crop suitability in Ghana, (ii) identify climate change impacts on crop climatic suitability for individual and multiple crops and (iii) determine crop diversification opportunities with maize, sorghum, cassava and groundnuts as key food crops.

2. Methods

2.1 Crop production data
Data used in modelling the climatic suitability were obtained from the Ministry of Food and Agriculture (MoFA)'s statistics department, which is an independent government organization that is responsible for collecting and compiling official agricultural statistics in Ghana. Crop yields for maize, sorghum, cassava and groundnut are reported in metric tons per hectare (dry mass). This is the ratio of total production per year in a district divided by total land cultivated for that crop in that district for that year. These datasets are obtained from the agricultural extension officers in each district who carry out crop cutting experiments to estimate production and cropped area annually. Yield data used were from 2006 to 2016.

2.2 Defining crop suitability classes
The production data for each of the four crops was split into four groups (optimal, moderate, marginal and limited) using percentiles of the average yield between 2006 and 2016 (Figure 1a). Optimal suitable areas
were defined as those areas that were above the 75th percentile of the mean yield of crop, representing areas with no significant limitations to sustained production and stability over time. Moderately suitable areas were those between the 50th and 75th percentile of the average yield, indicating areas with moderately severe limitations for sustained productivity or increased variability which increases the risk of crop failure. Marginally suitable areas had yield between the 25th and 50th percentile for the period, representing areas with severe limitations for sustained productivity, and pronounced variability between the years. Limited suitability areas are areas under the 25th percentile of the yield in the period, indicating areas where biophysical conditions are not apt for the crop, thus showing constantly low yields over time (Figure 1b). To ensure that data were in cropped areas, a NASA 2015 crop mask at 100m resolution was used as obtained from the Global Croplands database [42].

2.3 Biophysical variables for crop suitability

Eight biophysical parameters were used in modelling the climatic suitability of the four crops under current and future climatic conditions. These were total rainfall in the growing season, total rainfall received between March and September, sum of rainfall in the crop sowing month, rainfall coefficient of variation, diurnal temperature range between March and September, mean temperature growing season, mean temperature between March and September and top soil organic carbon (Table 1). The eight variables were selected because they are known to have major agronomic influence on the crops [43, 44]. The main growing period was defined as March to July in the South and end of May to September for the North according to distribution of rainfall and temperatures in Ghana [45] (Supplementary materials A1). The precipitation variables were derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) daily data at 0.05 degrees resolution from 2006 to 2016 [46]. Temperature variables were derived from the WFDEI Near Surface Temperature data for the same period at 0.5 degrees resolution [47]. Top soil organic carbon was obtained from ISIRIC [48].

For future climatic conditions, climatic variables were obtained from climate projections of the Inter-Sectoral Impact Model Inter-comparison Project (ISIMIP) for the period 2006 to 2016 and for 2041 to 2050. This climate data consisted of four different general circulation models (GCM) projections, namely GFDL-ESM2M [49, 50], HadGEM-ES2[51], IPSL-CM5A-LR [52], and MIROC-ESM-CHEM [53]. These GCMs were chosen because they are available with bias-adjustment [47, 54]. For future projections, the RCP2.6 and RCP8.5 scenarios were selected to represent the 1.5-2°C-target of the Paris Agreement and a scenario without climate policy, respectively, to capture the range of climatic possibilities (Table 2). The same soil organic carbon was used under current and future climate change. All these variables were
clipped to Ghana and then scaled, ensuring that they have a matching spatial resolution and extent. The same set of responses, predictors and scenarios were used for each crop and each scenario.

[Insert Table 1 near here]

2.4 Modelling approach
Suitability models or their variants have been used in assessing the geography of crop suitability and in modelling impacts of climate change on agriculture for different crops [28, 55-62]. To model the suitability classes of the four crops, we applied the eXtreme Gradient Boosting (XGBoost) machine learning approach to the variables. XGBoost is an improvement of the recursive tree-based partitioning method of gradient boosting by Friedman (63). The XGBoost approach developed by Chen and Guestrin (64) has been widely recognized as one of the best machine learning algorithms because it is fast, accurate and based on smaller models compared to similar family of models. Parameter tuning for automatically determining the number of rounds, maximum tree depth and sigma was done using the caret package [65] while the XGBoost was implemented with the xgboost package [66] using the multi:softmax objective in R (version 3.5). The input data was randomly split into 70% for model fitting (training and validation) and the remaining 30% for independent model testing.

2.5 Identifying determinants of suitability
The scaled importance or contribution of each variable to the suitability of each crop was determined by the difference between the full model and a set of permuted models lacking each variable in turn. Variable importance is determined by evaluating the effect of shuffling variables on the regularized gain. If the difference between the full model and a model without a specific variable is small, it is assumed that the relative importance of this variable is low and vice versa. The contribution of each variable is then standardized between 0 (lowest importance) and 1 (highest importance) [67]. This approach is widely used in selection of variables that are important for predicted variables in machine learning.

2.6 Model evaluation
We used the confusion matrix to assess the accuracy of the suitability modelling process relative to reference data. The overall accuracy (OA), kappa coefficient, multi-class AUC and class specific metrics (sensitivity, specificity, positive prediction value, negative prediction value, precision, recall, F1-score, prevalence, detection rate, detection prevalence and balanced accuracy) were used as calculated from the confusion matrix. OA is the percentage that indicates the probability that a grid cell is modelled correctly by the model relative to the known reference data. The OA is calculated by dividing the sum of the entries that form the major diagonal (i.e., the number of correct classes) by the total number of samples for each crop. The kappa coefficient ($k$) [68] measures the accuracy of the model predictions by comparing it with
the accuracy expected to occur by chance with $k$ values ranging from -1 (poor) to 1 (good) [30]. The multiclass area under receiver operating characteristic curve (AUC) was used to validate model fit by comparing and averaging all pairwise class AUC. Sensitivity for suitability class is the percentage of a category on the reference data that is correctly modelled as belonging to that category, and measures proportion of pixels omitted from a reference suitability class (omission error). Specificity expresses the proportion of a category on the reference data that is included erroneously in another suitability class (commission error) [69]. Other metrics used for class accuracy are described in full by Galdi and Tagliaferri (70) and Hossin and Sulaiman (71) This analysis was done in R v.3.3 (R Core Team, 2013).

2.6 Assessment of diversification potential

In order to determine the diversification potential for the four key food crops for Ghana, we combined the suitability of the crops to understand which areas are suitable for which crops and to what degree. At first the maps were combined to determine the number of crops that were suitable for each cell. To determine suitability for multiple crops, we summed the ranks of the modelled crop suitability with each class ranked from 1 (limited) to 4 (optimal). This produced diversification potential for the four scale from 4 (very low) to 16 (very high). After that, realizing that two-crop combinations were most frequently observed, further analysis of determining which combinations can be produced at each of the pixels was done through pairwise crop combinations and suitability determination. Pairs of crops were summed to produce a potential between 2 (very low) to 8 (very high). Changes in suitability proportion and distribution between the current and the projected climatic conditions were assessed by counting and comparing numbers and proportions of cells between times and scenarios.

3. Results

3.1 Model performance evaluation

To reliably assess crop suitability, we first evaluated the fit of the model on an independent test data set. There were differences in the model fit between crops, but all crops showed a good fit. The best accuracy was for modelling sorghum ($OA=0.82$, $k=0.75$ and $AUC=0.87$) (see Table 3). Modelling evaluation metrics for each of the four suitability classes such as sensitivity, specificity, positive and negative prediction values, precision, recall, F1-score, prevalence, detection rate, detection prevalence and balanced accuracy are shown in Supplementary materials, Table 1. These accuracy metrics indicated that the model
was able to match observed classes for all the crops and thus could be used with confidence in assessing
suitability of the four crops in Ghana under current and future climate.

[Insert Table 3 near here]

### 3.2 Identification of drivers of crop suitability

The relative contribution of each variable to modelling crop suitability was determined by analyzing the
importance of each variable to the model. The percent contributions of each variable to the explained
variability of each crop are shown in Figure 2. The suitability of each crop and its geographical range are
influenced by different biophysical parameters. The rainfall factors combined (sum of all three rainfall-
related factors) have a larger influence on the potential suitability for the four crops in Ghana compared to
the influence of temperature-based factors. These rainfall factors explain up to 60% of explained
variability of cassava, up to 59% the variability of groundnuts, 66% for maize and 57% the variability of
sorghum (Figure 2).

The total sum of rainfall received between March and September is more important in determining the
suitability of maize (25%), cassava (23%) and sorghum (19%). The mean temperature was not identified as
important for any crop, but the diurnal temperature range explains about a quarter of the suitability for
sorghum (26%), which is the highest value for any single variable. Variation of rainfall was important for
all crops in almost equal measure (12-16%), with more importance for maize. Soil organic carbon was
important (>10% contribution) for maize and cassava. The contribution of rainfall sum for sowing months,
growing season mean temperature and mean temperature between March and September to the suitability
of the four crops was mostly minimal (Figure 2).

[Insert Figure 2 near here]

### 3.3 Suitability and suitability changes of individual crops

Under current climatic conditions, the suitability of maize is very variable across the country with no
specific regional distribution. Optimal suitable areas for maize cover 23% of the country (Figure 3a,
Figure 4a). Under projected climatic conditions the areas that have optimal suitability for maize
production will decrease by 12% and by 14% under RCP2.6 and RCP8.5 respectively as suitability
transition from being optimal to moderately suitable and marginal. These are the largest changes from the
optimal suitable areas of the crops modelled in this study. Areas that have limited suitability are projected
to increase by 8% under RCP2.6 and by 7% under RCP8.5 scenario, with marginal areas decreasing by
11% (RCP82.6) and by 8% (RCP8.5) (Figure 3b-c, Figure 4a and Table 5).
Sorghum was modelled as having largest area for which it is optimally suitable (28%), which is the highest of the four crops for this category (Figure 3d, Figure 4b). Under climate change, the optimal suitability areas for sorghum are projected to decrease by 10% and 13% decrease under RCP2.6 and RCP8.5 respectively (Figure 3e-f, Figure 4b). Some parts of northern Ghana that have limited suitability for sorghum will become suitable under both RCP2.6 and RCP8.5 with an evident northwards shift in sorghum suitability under climate change. The areas that are unsuitable for sorghum are projected to increase by 12% (RCP2.6) and 13% (RCP8.5) by the 2050s (Figure 3e-f, Table 5).

Cassava was modelled as mostly suitable in the southern forested bimodal rainfall areas of Ghana (Figure 3g). Under RCP2.6, the results show that by the 2050s, optimal suitable areas for cassava will decrease by 7% while under RCP2.8.5, they will decrease by 9% (Figure 4c). Concurrently, the areas that have limited suitability for cassava will also slightly decrease by 4% under RCP2.6 and by 3% under RCP8.5 from the current 35%. The results showed that 48% of Ghana can produce groundnuts (optimal and moderate suitability) under current climatic conditions (Fig 3j. Optimal suitable areas (17%) are mostly located in the northern and central zones of Ghana (Figure 3k-l). Under projected climate change, the results show that the areas that have optimal suitability for groundnuts will decrease by 3% under RCP8.5 but will remain stable at 17% under RCP8.5, a trajectory different from other crops modelled in this study (Table 5, Figure 4d).

3.4 Diversification potential assessment for current and future climatic conditions

The suitability of each pixel for multiple crops was evaluated by determining the number of crops in each suitability class suitable for that pixel. Under all climatic conditions, none of the areas has optimal suitability for all the four crops in Ghana (Figure 5a). Under current climatic conditions, 2% of the country has moderate suitability for at least three of the four crops. This area is projected to remain unchanged under both RCP2.6 and RCP8.5 (Table 6, Figure 4b-c).

Similar significant decreases in suitability are also projected for areas that have moderate suitability for at least two of the four crops as these will decrease to 5% under RCP2.6 and 6% under RCP8.5. Much of these high suitable areas will become suitable for fewer crops under climate change as areas that are moderately suitable for all the four crops will increase to 1 % under both RCP2.6 and RCP8.5 while those
moderately suitable for two crops will increase from 19% to 24% (RCP2.6) and 25% (RCP8.5). Under both scenarios, the areas that are marginal for producing the four crops will increase from 1% under current climate to 3% (RCP2.6) or 1% (RCP8.5) of the country. Similarly, the areas that are marginal for two of the four crops will increase from 9% under current climatic conditions to 17% under RCP2.6 and RCP8.5, with a concurrent reduction in areas that are moderately suitable for just one crop as these become less (Figure 4b-c, Table 6).

We assessed the crop diversification potential under current and projected climatic conditions for pairwise combinations of crops across the country, as results indicated this to be the most promising diversification option (Figure 6). Areas with a highest potential for both crops in combination are 5.5% for maize and groundnuts, 5.4% for cassava and sorghum and 5.2% for maize and cassava (Figure 6, Figure 7, SI Table 4); all other combinations are below 5%. Except for cassava and groundnut combined, all combinations of crops are projected to decrease for the areas where both crops currently have the high suitability class. Concurrently, the areas where a combination of crops will be moderate and marginal or marginal for both crops will increase for both RCP2.6 and RCP8.5 (Figure 7). Although crop diversity opportunities vary across the country, aggregated results show the most promising crop combinations under climate change will be sorghum and groundnuts for the northern parts and cassava and groundnuts for the southern parts of Ghana. The least potential combination will be for cassava and sorghum, and groundnut and sorghum.

4. Discussion

The impacts of climate change on food security are multi-faceted. Therefore, in this study we quantified the impacts of climate change on the crop diversification potential by assessing the suitability of key food crops in the case of Ghana. A model for estimating crop suitability for maize, sorghum, cassava and groundnuts under current climate was constructed, which reliably reproduced observed suitability patterns. Therefore, we deem the model as sufficiently robust to predict the suitability of the four crops under future climate conditions. We identified individual and combined crop suitability for assessing areas with opportunities for crop diversification under current and projected climatic conditions.
4.1 Drivers of crop suitability and diversification potential in Ghana

Important biophysical predictors of the suitability of each crop were identified and these correspond to the reported crop requirements, growing conditions and spatial distribution of the four crops in Ghana [72-74]. The finding that precipitation-based factors are most important for the suitability of maize, sorghum and cassava is in line with other studies as rainfall remains the most important determinant of agricultural production in many African countries. For example, drought stress and related plant water availability constraints have been singled out as the most limiting factors for these crops in West Africa and elsewhere[75-79], particularly as these crops are almost entirely produced under rain-fed conditions.

Although rainfall amounts are generally high in Ghana (over 800mm in most years), precipitation remains an important factor in determining crop potential. This is because of the climate gradient in Ghana from the south to the north, and its intra-seasonal variation influencing the suitability of the different crops. For comparison, in China He and Zhou (80) found temperature-related variables as more important factors for maize suitability than precipitation, highlighting the local relevance of our results that cannot simply be extrapolated. We found that sorghum suitability is also influenced by the diurnal temperature range, which concurs with current understanding that sorghum is a more adverse weather tolerant crop. This tolerance is enabled by heterotic mechanisms that allow for greater biomass and yield production at a shorter period, ‘stay green’ mechanisms, and lodging and desiccation tolerance compared to other crops [81, 82].

4.2 Crop suitability and diversification potential under climate change

Of the four crops, groundnuts are the most resilient under climate change, showing the smallest loss in suitable growing areas. This could be explained by groundnuts being legumes with a short growth period and whose harvested parts grow below ground and thus are partly protected by the soil from direct effects of warming. Groundnut viability is closely related to rainfall patterns [83, 84], particularly the amount of rainfall in the growing season due to the less extensive root system, and thus projected increases in rainfall can directly increase suitability for groundnut production. This is especially so as the assessment of changes in agronomic variables show increased rainfall variability than changes in total values. These results concur with findings by earlier studies on the potential impacts of climate change in Ghana which reported groundnuts as less impacted compared to other food crops [85]. Our findings show that sorghum remains a high potential crop in the northern parts of Ghana under a changed climate, as limited areas in these areas decrease. This result underlines the importance of sorghum, which is already a major food crop in the northern parts of Ghana.

The greatest climate change risk was identified for maize which is the crop with the most planted area and the highest net consumption in the country [86]. Apart from the reliance of maize production on rainfall in
In addition to these crop-specific climate responses, the predominant outcome of the suitability modeling is that the impacts of climate change are site and crop-specific. The impacts are determined by both the biophysical factors that influence crop viability and the specific genetic characteristics of the crops. Shifts in crop suitability have been identified as a key influence of climate change, spurring a need for adequate adaptation measures in the identified areas or planning for food transfer systems that distribute food between the areas that will become suitable and those that will become marginal for a particular crop [35, 89].

This study indicates that there will be a reduction in the possibility of crop diversification in Ghana under climate change. Areas which are currently optimally and moderately suitable for production of the four crops will decrease while areas marginally and moderately suitable for more crops will increase. This reduced potential for crop diversification under climate change erodes the synergistic interactive benefits farmers gain from crop diversification. For example, crop diversification is not only a strategy for increasing crop yields but it is a mitigating factor for risks, including those that are weather related [90-94]. Crop diversity therefore decreases vulnerability of the agricultural enterprise to climate change through increased crop yields on one hand and heightened positive economic outcomes associated with hedging against volatility in the agricultural commodity markets on the other hand.

Furthermore, the finding that two crop combinations involving sorghum and groundnuts for the north and maize and groundnuts for the south have the most potential under climate change is important for adaptation planning and investment in these crops. As concluded by Altieri and Nicholls (95) that more diverse cropping systems are more resistant to disturbance and more resilient to environmental perturbations derived from extreme climatic events, these combinations can be promoted for farmers in Ghana who are experiencing either extreme or decreasing rainfall patterns and increasing temperature variability.

There are a number of adaptation measures that can be applied to increase diverse crop production systems at field, farm, landscape, regional or national scales to avert the modelled reduced potential. At
field or farm scale, economic stimulus for farmers to grow diverse crops are required to enable farmers to transition to these more resilient systems. Lin (96) suggest that economic models that can predict threshold prices at which farmers begin to adopt diverse systems or payments for ecosystem services obtained from diversified systems can be effective in persuading many farmers to adopt crop diversification. Altieri and Nicholls (95) posit that smart agricultural systems such as raised beds and semi-permanent water collecting basins that act as field-scale micro-catchments can sustain production of different crops under climate change as they can work for most crops. These and other conservation agriculture techniques could improve potential for diverse crops. This is especially important as rainfed agricultural systems are projected to remain dominant in African agricultural systems [97]. While these have potential, they should not add to complexity of already complex agricultural systems in Ghana and other African countries [98] through, for example, increasing labor burden [99, 100]. At national scale, policies encouraging the production of multiple crops such as development of market incentives for many crops can also help promote diversification. Shifting extension advice from individual crops to multiple crops could be an important first entry point.

4.5 Considerations in the interpretation of the results of crop suitability modelling

There are some limitations and potential sources of uncertainty that should be considered in the interpretation of our results. The suitability models are driven by climate data and current crop production data, which have inherent uncertainties. Future projections of crop production suitability are produced by combining suitability models with projections based on GCMs that describe potential future conditions. These different GCMs rely on different parameters and incorporate different functions to cover the dynamics of atmospheric circulation, ocean effects, or feedbacks between the land surface and the atmosphere. Therefore, they are prone to disagreements or errors that will be propagated in the modelling. Our modelling omitted direct physiological interaction effects in multiple crops such as nitrogen fixation, water retention, pollination, completion or competition for nutrients that cannot be captured by this type of modelling. The area suitability calculations also include other land that may not be available for agricultural production. These other land areas are, for instance, urban areas, protected areas and riparian zones which cannot be removed at the spatial resolution of the datasets used. Thus, interpretation should be on the relative change rather than the absolute change in area suitable for each crop.

5. Conclusion

In this study we provide a quantitative starting point to gauge future potentials of crop diversification as a strategy to build climate resilient agricultural systems that are not available elsewhere. We conclude that impacts of climate change on different crops, regions and climatic scenarios are uneven, and highlight the crops and areas that are likely to be impacted the most. From such information, the types, scale and
urgency of investing into adaptation strategies in the light of the NDC and NAP implementation process can be guided accordingly. Thus, our approach identified local impacts across the entire country that could be more useful for adaptation planning in ecologically, culturally and socio-economically heterogeneous farming systems such as in Ghana. In addition, and maybe more importantly, our integrated approach that assessed crop diversification potential implicitly captured opportunities and losses of many co-benefits that can be gained from crop diversification which are common in tropical countries but are not captured or indicated in individual crop assessments. The results from this study provide a scientific basis on which a national-level risk assessment on the impacts of climate change on crop diversification can be implemented. Since the information in this study is spatially explicit, areas requiring prioritization in adaptation action can be identified as those to experience the largest changes in area suitability and number of suitable crops. There is a chance that the impacts of climate change could be reduced through systematic planning for climate-adapted diversification. This is, to our best knowledge, the first study to assess the impacts of climate change on crop diversification quantitatively at this resolution for a whole country.

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Competing Interests
Authors declare no conflict of interests.

Data availability
Data used in the analysis is curated on Zenodo (https://www.zenodo.org/)

Supplementary materials
Attached separately
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### Table 1: The eight biophysical variables used for crop suitability modelling and their descriptions and derivations from daily weather data

| Variable | Description* |
|----------|--------------|
| Total rainfall in the growing season | Sum of rainfall for 24 May (DOY = 145) to 30 September (JD = 274) for the north and 1 March (JD = 61) to 30 June in the south. |
| Total rainfall received between March and September | Sum of rainfall received from 1 March (DOY = 61) to 30 September (DOY = 274) to represent the whole growing season for both north and south. |
| Sum of rainfall in the crop sowing month | Sum of rainfall received from 24 May to 30 June (DOY = 182) in the north and 1 March (DOY = 61) to 30 April (DOY = 121) in the south. |
| Rainfall coefficient of variation | The ratio of the standard deviation of the monthly sums of rainfall between March and September to the mean monthly rainfall. |
| Diurnal temperature range between March and September | The average of the differences between maximum temperature and minimum temperature from 1 March (DOY = 61) to 30 September (DOY = 274). |
| Mean temperature growing season | Average temperature between 24 May to 30 September (JD = 274) for the north and 1 March (DOY = 61) to 30 June (DOY = 182) in the south. |
| Mean temperature between March and September | Average temperature between 1 March (DOY = 61) to 30 September (DOY = 274) to represent the whole growing season for both north and south. |
| Top soil organic carbon | The amount of organic carbon in the top 5cm of the soil per ha. |

* DOY is Day of Year

### Table 2: Projected rainfall and temperature changes as used in the suitability modelling under the RCP2.6 and RCP8.5 for Ghana. Variables are summarized across the country.

| Scenario | Model | Sum rainfall Mar - Sept(mm) | Sum rain sowing month(mm) | Rainfall coefficient of variation (%) | Rainfall growing season(mm) | Average Tmax - Tmin (°C) | Mean temperature growing season (°C) | Mean temperature Mar-Sept (°C) |
|----------|-------|-----------------------------|---------------------------|---------------------------------------|-----------------------------|---------------------------|------------------------------------|-------------------------------|
| Current  | Current | 1246 | 228 | 69 | 558 | 9.9 | 24.5 | 25.7 |
| RCP2.6   | GFDL   | +52 | +2 | -2 | +30 | -0.4 | +1.5 | +1.3 |
|          | IPSL   | -43 | +3 | +3 | -14 | -0.2 | +1.8 | +1.5 |
|          | HADGEM | -4 | +10 | +3 | +14 | -0.3 | +2.2 | +1.4 |
|          | MIROC  | +58 | +21 | +6 | +41 | -0.4 | +1.1 | +1.3 |
|          | Model mean | +16 | +9 | +3 | +18 | -0.3 | +1.7 | +1.4 |
| RCP8.5   | GFDL   | +59 | +27 | +3 | +40 | -0.7 | +2.1 | +2.5 |
|          | IPSL   | -117 | -3 | +2 | -29 | -0.1 | +2.8 | +2.6 |
|          | HADGEM | -13 | +10 | +3 | +7 | -0.5 | +1.5 | +2.5 |
|          | MIROC  | +86 | +21 | +2 | +51 | -0.3 | +2.3 | +1.8 |
|          | Model mean | +3.8 | +13.9 | +2.8 | +17.5 | -0.4 | +2.2 | +2.3 |
Table 3: Overall accuracy, kappa and multi-class AUC values as indicators model performance for maize, sorghum, groundnut and cassava in determining crop suitability classes in Ghana.

| Crop       | Accuracy | Kappa | Multiclass-AUC |
|------------|----------|-------|----------------|
| Maize      | 0.75     | 0.66  | 0.81           |
| Sorghum    | 0.82     | 0.75  | 0.87           |
| Groundnuts | 0.75     | 0.66  | 0.85           |
| Cassava    | 0.71     | 0.59  | 0.84           |

Table 5: Mean percentage changes in area suitable for each suitability class under climate change for maize, sorghum, cassava and groundnuts.

| Crop       | Maize | Sorghum | Cassava | Groundnut |
|------------|-------|---------|---------|-----------|
| Suitability| RCP2.6| RCP8.5  | RCP2.6  | RCP8.5    | RCP2.6  | RCP8.5 |
| Limited    | -10.6 | -8.2    | -11.8   | -9.4      | -3.7    | -2.8   | -7.6    | -7.1    |
| Marginal   | 8.1   | 6.6     | 12.1    | 12.7      | 5.2     | 4.2    | 11      | 4.5     |
| Moderate   | 14.4  | 15.5    | 9.3     | 9.7       | 5.6     | 8.2    | 0.4     | 2.1     |
| Optimal    | -11.9 | -14.0   | -9.7    | -13.1     | -7.2    | -9.6   | -3.8    | 0.4     |

Table 6: Area fractions for the suitability of multiple crops in Ghana under current and future climates

| Suitability | High | Moderate | Marginal | Limited |
|-------------|------|----------|----------|---------|
| Crops       | Current | RCP26 | RCP85 | RCP26 | RCP85 | Current | RCP26 | RCP85 | Current | RCP26 | RCP85 |
| One         | 41    | 29     | 33.2    | 43.9   | 45.1   | 43.5    | 37.4   | 36.6   | 26.3    | 31.1   | 25.6  | 32.5 |
| Two         | 18    | 5.4    | 5.6     | 18.6   | 24.0   | 25.1    | 27.3   | 32.5   | 26.1    | 25.0   | 16.1  | 12.3 |
| Three       | 1.6   | 0.1    | 0.1     | 2.3    | 8.5    | 7.9     | 9.2    | 16.7   | 17.1    | 5.5    | 1.6   | 5.9  |
| Four        | 0.0   | 0.0    | 0.0     | 0.0    | 1.3    | 1.4     | 0.7    | 3.2    | 1.3     | 0.6    | 1.6   | 0.0  |
**Figures captions**

Figure 1: (a) Trends in yield for maize, sorghum, groundnut and cassava in Ghana from 2006 to 2016. (b) The 11 year mean crop yield distribution for each of the four suitability classes across all districts. The right axis in (a, b) is for cassava yields only.

Figure 2: Variable importance of each of the parameters used in determining the suitability for maize, sorghum, groundnut, and cassava in Ghana.

Figure 3: Suitability for (a) maize under current conditions (b) maize by 2050 under the RCP2.6, (c) maize under RCP8.5, (d) sorghum under current conditions (e) sorghum in 2050 under RCP2.6 in Ghana under (f) sorghum under RCP8.5, (g) cassava under current conditions (h) cassava in 2050 under RCP2.6 in Ghana under (i) cassava under RCP8.5, (j) groundnuts under current conditions (k) groundnuts in 2050 under RCP2.6 in Ghana under (l) groundnuts under RCP8.5.

Figure 4: Assessment of changes in suitability according to the applied GCMs and RCP for (a) maize (b) sorghum, (c) cassava and (d) groundnuts in Ghana.

Figure 5: Modelled suitability four crops under (a) current (b) RCP2.6 and (c) RCP8.5 climatic conditions for Ghana.

Figure 6: Maps showing the diversification potential for pairwise crop combinations across Ghana under current, RCP2.6 and RCP8.5 climatic scenarios.

Figure 7: Area fractions suitable for (a) maize and sorghum (b) Maize and cassava (c) Maize and Groundnut (d) Cassava and Sorghum, (e) cassava and groundnut and (f) Sorghum and groundnut. The lines are Gaussian distribution fit for each climatic scenario. Ld-Ld is for limited suitability for both crops, Ld-Mg is area with limited for one of the 2 crops and marginal for the other, Mg-Mg is area where both crops are marginal, Mg-Md is area that is marginal for one crop while moderately suitable for the other crop, Md-Md is where both crops are moderately suitable, Md-Op is where one crop is moderately suitable and the other has optimal suitability and Op-Op is where both crops are optimally suitable.
Figure 1
Figure 4
