1   Where are commodity crops certified, and what does it mean for conservation

2   and poverty alleviation?

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4   **Running title:** Mapping certified commodity crops

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Abstract

Voluntary sustainability standards have expanded dramatically over the last decade. In the agricultural sector, such standards aim to ensure environmentally and socially sustainable production of a variety of commodity crops. However, little is known about where agricultural certification operates and whether certified lands are best located for conserving the world's most important biodiversity and benefiting the most vulnerable producers. To examine these questions we developed the first global map of commodity crop certification, synthesizing data from over one million farms to reveal the distribution of certification in unprecedented detail. It highlights both geographical clusters of certification as well as spatial bias in the location of certification with respect to environmental, livelihood and physical variables. Excluding organic certification, for which spatial data were not available, most certification of commodity crops is in tropical regions. Certification appears to be concentrated in areas important for biodiversity conservation, but not in those areas most in need of poverty alleviation, although there were exceptions to each of these patterns. We argue that the impact of sustainability standards could be increased by identifying places where it would be most beneficial to strengthen, consolidate, and expand certification. To achieve this, standards organizations will need to undertake more rigorous collection of spatial data, and more detailed analysis of their existing reach and impacts, with attention to potential trade-offs between different objectives. Efforts to promote spatial prioritization will require new partnerships to align specific conservation aims with the interests and capabilities of farmers.

Introduction

Improving the environmental and social sustainability of agriculture is an ongoing challenge worldwide (Tilman and Clark, 2015). Governments have responded to this challenge by developing legislation and initiatives such as agri-environment schemes (Batáry et al., 2015). Alongside these government-led initiatives, the work of multiple stakeholders has led to the creation and promotion of voluntary sustainability standards systems, also referred to as certification schemes (Potts et al., 2014; Rueda et al., 2017). These standards typically define the practices of sustainable agriculture, and identify actions producers must take to be certified as environmentally and socially responsible (Milder et al., 2015). Over the last decade, there has been a near-exponential increase in area managed under certification (Tayleur et al., 2016). Certification is often promoted as a way for individual consumers to make more ethical purchasing decisions (Dauvergne and Lister, 2010). It is also proposed as a way to mitigate negative impacts of commodity production and improve the wellbeing of farmers and farm workers in the developing world (Lenzen et al., 2012). Many multi-national companies now use certification to help achieve and demonstrate progress towards public sustainability commitments (Dauvergne and Lister, 2012; Levin and Stevenson, 2012). Land under certification has also been adopted as an indicator of progress towards Aichi Target 7, which calls for "areas under agriculture... [to be] managed sustainably" by 2020 (Tittensor et al., 2014). Impact evaluations, while still sparse, suggest that standards are likely to vary considerably in their effectiveness. The need for more widespread and systematic evaluation of impacts – taking account of issues such as selection bias in recruitment of farmers – is well established and has been discussed in detail elsewhere (Blackman and Rivera, 2011; Milder et al., 2015). Although there is a need for improved evaluations, there is accumulating evidence (reviewed by Milder and Newsom, 2015; Steering Committee of the State of Knowledge Assessment of Standards and Certification, 2012; Tscharntke et al., 2015) that certification can contribute to both conservation and livelihood benefits. The analyses that follow are grounded in the assumption that certification can make such a contribution.

77   Despite the increasing prominence of certification, there is little information about its geographical

78   distribution at sub-national scale. Globally, certification is estimated to cover just 1.1% of all

79   cropland (Tayleur et al., 2016). Because coverage is limited, it is crucial that certification is targeted

80   towards those areas where it can have most impact or additionality (Garrett et al., 2016), in line with

81   the priorities and criteria of different standards. For example, standards whose priority is to reduce

82   social inequality, such as Fairtrade, may wish to know whether they are reaching the poorest

83   farmers, while those that also prioritize biodiversity conservation, such as Rainforest Alliance/SAN,

84   may wish to know that they are certifying farmers in areas important for conservation. Other

85   factors, such as literacy or a supportive policy environment, as well as consideration of other

86   possible interventions, will also influence where certification is most appropriate and feasible. While

87   crop-specific schemes include some unique criteria – such as restrictions on planting oil palm on

88   peatland – there has also been some convergence of standards, and most schemes now include both

89   environmental and social criteria (UNEP-WCMC, 2011). Therefore, most standards have some

90   capacity to address biodiversity conservation, habitat loss (including deforestation) and livelihood

91   protection, although they differ considerably in their specific requirements and in how these are

92   implemented and audited (Tayleur et al., 2016).

93   *What influences the spatial distribution of certification?*

94   To the extent that spatial targeting of certification can be said to have occurred to date, it has largely

95   been a by-product of the management of specific supply chains (Garrett et al., 2016; Getz and

96   Shreck, 2006; Renard, 2010; Vellema et al., 2015). Companies that have committed to responsible

97   practices have worked to ensure that those producing the agricultural commodities they use are

98   certified. Some of these efforts have been reactive, responding to civil society campaigns, regulatory

99   requirements, or anticipation of campaigns or regulations. Others have been more proactive, aiming

100   to increase the security or quality of commodity supply, or reputational benefits to a company's

101   brand. Such efforts reflect to some extent the imperative to target certification to places of greatest

102   social and environmental risk. For instance, civil society campaigns have highlighted egregious

103   instances of deforestation and infringements of community rights. Another mechanism is the use of

104   certification as a policy proxy by governments. For instance, the US state of Pennsylvania obtains FSC

105   certification for its state forests, and some government procurement policies preference or require

106   responsibly sourced products, including certified products (Steering Committee of the State of

107   Knowledge Assessment of Standards and Certification, 2012). Although indirect and often reactive,

108   both supply chain commitments and procurement policies therefore offer some opportunities to

109   effect spatial targeting. The creation of sustainability standards focused on specific crops implicated

110   in environmental and social problems has also resulted in spatial targeting at a very coarse scale (it is

111   notable that all of the certification schemes for which we obtained data are concentrated in tropical

112   countries).

113   Despite these examples, there do not yet appear to have been coordinated strategic efforts to

114   systematically identify the places where the impact of certification could be greatest. There are

115   considerable opportunities to do so, to identify priorities for future civil society campaigns,

116   corporate efforts, and government interventions. Currently, at the country level, agricultural

117   certification has poor representation in the world's 31 poorest countries (those classified by the

118   World Bank as low income) and for staple crops of low export value (Tayleur et al., 2016).

119   Analogously, within the forestry sector, certification has been criticized for failing to protect tropical

120   forests that are most at risk, with the majority of certified wood coming from temperate developed

121   countries (Gullison, 2003). Without a more strategic approach to strengthening, consolidating, and

122   expanding agricultural certification, there is a risk that it may not reach those areas and producers

123   where the greatest additionality can be gained.

124   *Spatial prioritization as a conservation and poverty alleviation tool*

125   While global coverage of certification is still limited, its rapid uptake by producers of some of the

126   most environmentally-damaging commodity crops indicates its potential to contribute to

127   conservation and development. Given sparse resources, certification, like other voluntary incentive

128   schemes, should be prioritized to where its introduction could have most additional beneficial

129   impact (Wünscher et al., 2008). One of the few studies to explore how well standards are targeted

130   found that adoption of two schemes (the Round Table on Responsible Soy (RTRS) and the

131   Roundtable on Sustainable Palm Oil (RSPO)) was better directed towards places where they could

132   reduce deforestation in some countries but less so in others, and that the standards were

133   disproportionately adopted by large producers rather than smallholders (Garrett et al., 2016). While

134   there has been some targeting of high-risk commodities for certification such as palm oil and

135   soybeans, little is known about whether certification reaches those areas of greatest conservation

136   and poverty alleviation need within the global ranges of these crops. Although the areas of greatest

137   need are not always those where certification can have most impact – because supporting

138   conditions for certification also vary, and alternative interventions may sometimes be more effective

139   – identifying such areas provides an initial basis for spatial targeting.

140   We aimed to: (1) develop the first detailed global map showing where certification is located,

141   synthesizing data from all of the main standards for which data were available; and (2) characterize

142   biodiversity and poverty in landscapes in which certification currently operates, globally, regionally

143   and within countries, using as case studies crops for which sufficient data exist. We use these

144   analyses to illustrate methods for identifying priority areas that could be targeted to maximize the

145   incremental benefits of improving, consolidating, and expanding certification, and outline how doing

146   so could increase the contribution of certification to global sustainability. We have assumed that the

147   expansion of certification has been too recent and limited to have yet had a detectable influence on

148   the biodiversity and poverty datasets we used, and our analysis should thus be interpreted as an aid

149   to priority-setting, rather than implying any causal influence of certification on these variables.

150

151   **Materials & Methods**

152   *Obtaining spatial data on certified producers*

153   Data on the spatial location of certified farms were obtained through publicly available datasets and

154   via direct approaches to standards bodies (see Supplementary Materials for details). We sought data

155   from all major standards and codes of practice covering the certified commodity crops with the

156   highest levels of certification: banana, cocoa, coffee, cotton, tea, soybean, sugar, and palm oil (Potts

157   et al., 2014). The scope of the data search was not limited to any particular geography, but the

158   standards for which data were available operate primarily in tropical countries. Not all schemes

159   were able or willing to provide data (see Supplementary Materials for details). In some cases,

160   permission was granted only on condition that data were used in aggregate with other standards so

161   that the specific locations for individual schemes and producers could not be identified. To meet this

162   requirement our maps are at the resolution of 30 km × 30 km cells, after first standardizing all data

163   by converting them into point localities. The format of data available from each standard varied

164   considerably: while most were able to provide a coordinate for each certificate, a few schemes had

165   postal address data only. RSPO was the only standard that routinely collects polygon data outlining

166   plantation boundaries. Usable spatial data were not available for certified cotton, so this commodity

167   was excluded from further analyses.

168   *Validation and standardization of spatial certification data*

169   Several factors influenced the accuracy of the spatial data: 1) In some standards, multiple farms (e.g.

170   within a co-operative) are represented by a single certificate and coordinate, often referred to as a

171   'group certificate'; 2) Occasionally the coordinate for a certificate is associated with an

172   administrative office rather than the actual farm; 3) Some farms hold multiple certifications, e.g.

173   Rainforest Alliance/SAN and Fairtrade, but because spatial data are often imprecise, many certified

174   farms are small, and common identifiers are not used across standards, such overlaps cannot be

175   identified by spatial coincidence of points. We converted address data into point locations using the

176   ESRI Online World Geocode service which identified coordinates for 23% of all addresses entered.

177   We tested the sensitivity of our results to the inclusion of these data by repeating analyses with and

178   without them. As certification patterns did not change significantly, we report the results including

179   the geocoded data.

180   To improve accuracy, we undertook a number of data cleaning steps. First we checked whether the

181   coordinate location corresponded to the country named in the accompanying metadata. Where

182   points were not located in the correct country, simple transformations (swapping latitude and

183   longitude, and hemisphere) were attempted. If this did not locate the coordinate in the correct

184   country, the point was discarded. Points that did not fall within the relevant crop growing area as

185   defined by our crop map (see *Crop Cover*) were also discarded. Excluding the geocoded address data

186   mentioned above, 93% of the data provided met these validation requirements.

187   To account for spatial inaccuracies and to protect the privacy of individual producers, we

188   summarized data using 30 km × 30 km grid cells created with the Fishnet tool in ArcMap 10.2 using

189   an equal-area projection. Each grid cell was classified as either containing certified land or not.

190   *Biodiversity variables*

191   We obtained breeding range maps for all the world's amphibians and mammals (IUCN, 2014) and

192   birds (BirdLife International and Natureserve, 2014). We excluded parts of species' ranges where

193   they have been extirpated, as well as areas where they are not native. We determined the potential

194   presence/absence of each species in each 30-km cell using *gIntersects* in the *rgeos* package (Bivand

195   et al., 2016) in R (R Development Core Team, 2016). The range maps represent the distribution

196   boundaries and are likely to contain commission and omission errors (Rodrigues et al., 2004), but

197   these were minimized by our use of 30-km cells. We calculated a metric of the importance of each

198   grid cell for biodiversity by summing the inverse range size for each species present. Using this

199   metric, a cell would receive a value of 1 for a species if it contained its entire global distribution, and

200   a value of 0.0001 if it was one of 10,000 cells within the distribution of the species. The metric is a

201   measure of the relative contribution each cell makes to global biodiversity (of the three vertebrate

202   groups considered), and is thus indicative of the global conservation value of each cell.

203   In addition to species range maps we obtained shapefiles from the World Database on Protected

204   Areas (IUCN and UNEP-WCMC, 2015) as well as shapefiles for Important Bird and Biodiversity Areas

205   (IBAs; sites of international significance for birds) (BirdLife International, 2015). For both of these

206   datasets we calculated the percentage cover within each 30-km grid cell in ArcMap.

207   *Deforestation*

208   High-resolution maps of Global Forest Change (GFC) were obtained from Hansen et al. (2013). These

209   maps were derived from Landsat imagery and were accessed via the cloud computing environment,

210   Google Earth Engine (Google Earth Engine Team, 2015). The GFC maps report annual loss and gross

211   gain in tree cover during the period 2000-2012, at 30-m resolution. We also used the

212   "treecover2000" map from Hansen et al. (2013), representing the percentage tree cover in the year

213   2000. We combined this with the "lossyear" map to identify pixels which lost their tree cover during

214   2000-2012. We estimated the area of tree cover lost in each 30-m pixel, following Hansen et al.

215   (2013). We used the Google Earth Engine platform to process the data, after first resampling to a

216   resolution of 200 m (see Tracewski et al., 2016 for more details). These data were then summarized

217   for every 30-km grid cell as the percentage of original tree cover lost within the grid cell, and this

218   was converted to an average annual rate of net tree cover loss. This metric provides a proxy for

219   deforestation of natural forest, but may also include tree cover loss and gain in plantations.

220   *Crop cover*

221   The mean percentage of crop cover for each 30-km grid cell was calculated using the value from

222   Monfreda et al. (2008) who provide estimates for the year 2000. In instances when sub-country yield

223   statistics were not available, Monfreda et al. averaged country level yields over large areas leading

224   to obvious errors in crop distribution. For example, their maps show cocoa growing across Ghana

225   despite this crop in reality being excluded from the arid northern two-thirds of the country.

226   Therefore we used the Global Agro-Ecological Zone climatic suitability maps (IIASA/FAO, 2012) to

227   clip the Monfreda maps to define the likely limits of crop production.

228   *Variables relevant to poverty alleviation*

229   We chose three variables for which global spatial data at a fine-scale resolution were available. The

230   first was mean travel time to closest city of >50,000 people as calculated by Nelson (2008) in his

231   global map of accessibility, which we used as a proxy for market access. Secondly, we calculated the

232   mean percentage of the population in poverty for each 30-km grid cell using the global poverty map

233   created by Elvidge et al. (2009) from satellite data on night-time lighting. Finally we calculated mean

234   field size for each 30-km grid cell as calculated by Fritz et al. (2015). Field size has been shown to

235   correlate with farm size (Levin, 2006) and so we used grid cells with small field sizes as a proxy for

236   the presence of smallholder farmers.

237   *Other variables*

238   To investigate other factors that might characterize or influence the location of certified crops we

239   also calculated mean altitude and slope from the global SRTM dataset (USGS, 2004).

240   *Analyses*

241   We used bootstrap resampling tests to examine patterns in those grid cells containing certification

242   versus those that did not, for a number of different variables. Because data were summarized at the

243   30-km scale, covariate values within each grid cell could not be attributed directly to certified farms,

244   so our tests examined how the local landscapes in which certification exists differ compared to non-

245   certified landscapes, without implying causation. To run the resampling tests we first defined our

246   certified sample as all the 30-km grid cells containing certified farms for each crop. The test statistic

247   was then calculated as the mean of covariate values from the certified sample. To create our test

248   distribution we then obtained a random sub-sample without replacement from non-certified grid

249   cells of the same size as our certified sample and calculated the mean for the sub-sample. We

250   sampled without replacement as we were using a finite population. We weighted the probability of

251   a grid cell being included in the random sample by the proportion cover of the commodity crop of

252   interest. This allowed us to generate the values that might be expected for each variable if

253 certification was located randomly within the distribution of each crop. We ran our resampling

254 routine using the wrswoR package in R (Müller, 2016). We repeated the resampling procedure

255 10,000 times in order to create our test distribution and then calculated the quantile in which our

256 test statistic fell. Our test was two-tailed as we had no prior expectation as to whether certified

257 values would be higher or lower than non-certified, so we considered anything below 2.5% or above

258 97.5% significant.

259 We carried out our bootstrap resampling tests at the global level to examine broad biases in the

260 spatial distribution of certification. To examine regional and within-country spatial bias we then

261 examined a subset of three commodities with the highest levels of certification in those

262 geographical regions in which their certification was concentrated: coffee in Central America, cocoa

263 in West and Central Africa and palm oil in Southeast Asia (details in Supplementary Materials). When

264 examining certification patterns within countries, only 30-km grid cells that fell wholly within the

265 country were included. Patterns within countries were examined only when there were more than

266 six certified cells and when the number of certified cells was not greater than the number of non-

267 certified.

268

269 **Results**

270 Across all standards we mapped a total of 84,853 individual and group certificates covering

271 1,042,734 farms. Once we restricted our data to the primary commodity crops of interest, this

272 reduced to 83,860 certificates, and after validation, to 78,544. A list of all certified crops is provided

273 in the supplementary materials. When summarized at the 30-km scale, 1873 cells contained certified

274 farms out of 45,717 cells where these crops were cultivated (4.1%, Fig. 1). Global levels of

275 certification were highest for coffee (at 9.0% of coffee-growing cells) but much lower for other crops

276 (banana: 0.3%, cocoa: 2.2%, oil palm: 2.2%, sugarcane: 0.6%, soy: 0.2%, tea: 2.0%). There were clear

277   large-scale aggregations of certification in Central America, Brazil, West Africa, parts of East Africa

278   and Southeast Asia.

279   *Global certification coverage by crop*

280   The distribution of grid cells containing certification in relation to our variables of interest varied

281   considerably between crops (Table 1). For some crops, cells with certification coincided with higher

282   importance for biodiversity conservation than was typical of cells with the same crop without

283   certification. Certified coffee, tea, and cocoa all occurred in cells with higher importance for birds, on

284   average, than that in non-certified cells. The distribution of coffee, both certified and not, included

285   areas of particularly high conservation importance for birds (Figure 2). Certified tea occurred in cells

286   with higher importance for amphibians, while the soy production cells with highest amphibian value

287   were less likely to be certified. For mammals, coffee certification occurred in cells with higher

288   conservation importance than that in coffee cells without certification. However, for all other crop-

289   taxon combinations, there were no significant differences between cells with certification and

290   without, in respect to their importance for birds, amphibians or mammals.

291   Certified tea occurred on average in grid cells with greater protected area coverage, while certified

292   oil palm and coffee occurred in cells with less protected area coverage than non-certified cells. Cells

293   with certified tea coincided to a greater extent with IBAs than non-certified cells, while cells with

294   certified cocoa had less overlap with IBAs than non-certified cells. There were differing patterns

295   between crops with respect to rates of tree cover loss. Cells with certified soy, oil palm, or cocoa

296   coincided with higher rates of loss, while cells with certified coffee or tea coincided with lower rates

297   of loss compared to cells growing uncertified crops of the same type.

298   For most crops, grid cells with certification tended to have larger fields, be closer to market towns,

299   and have a lower percentage of the population in poverty than the distribution of the crop more

300   generally. Although cells with certified soy tended to have larger field sizes, they were also further

301   from towns, and in poorer areas. Certified cocoa was found in cells with smaller field sizes, although

302   still closer to towns, and in wealthier areas than non-certified cocoa. Physically, certified crops often

303   occupied cells with significantly different (higher, lower, or similar, depending on the crop) altitude,

304   slope, and crop cover compared to the crops' global distributions (Table 1).

305   *Case study: Cocoa in West and Central Africa*

306   We explored the extent to which these global patterns persist at regional and national scales,

307   focusing on three data-rich case study areas. Across the West and Central African cocoa-growing

308   region, Cameroon, Cote d'Ivoire, Ghana, Nigeria, Sierra Leone, and Togo all grew certified cocoa,

309   although certification was restricted to only a single grid cell in Togo and two in Sierra Leone. Across

310   the region as a whole, cells with certified cocoa had similar importance for birds to cocoa cells

311   without certification. The global-level pattern of higher importance for birds in certified cells was

312   reflected in some countries (Côte d'Ivoire, Ghana and Cameroon), but not in Nigeria (Table 2). For

313   amphibians, certified cells had higher importance in some countries, but not globally or across the

314   West African cocoa-growing region as a whole. For mammals, cells with certified cocoa had higher

315   conservation value at a regional level in West Africa, and in most of the cocoa-growing countries

316   within it, whereas at a global level there was no difference from cells without certification.

317   In West Africa as a whole, grid cells with certified cocoa did not have significantly greater cover of

318   either protected areas or IBAs but were closer to market towns and had lower levels of poverty.

319   When examining patterns in individual countries, cells with certification tended to have higher

320   conservation value and to occur closer to towns and in areas of lower poverty than cocoa-growing

321   cells without certification. Landscapes with certification tended to be in grid cells with lower levels of

322   cocoa cover than the control. Patterns at the country level were not always reflected at the regional

323   (West Africa) level. For example, cells with certified cocoa had higher importance for birds and

324   amphibians for three of the four countries examined in Table 2, but no significant relationship was

325   found at the regional level, likely because of variation within and between countries.

326   *Case study: Coffee in Central America*

327 Grid cells containing certified coffee are most prevalent in several Central American countries (Costa

328 Rica, El Salvador, and Guatemala), outnumbering non-certified coffee-growing cells. In the remaining

329 countries, certification presence is still high with the exception of Panama where it is absent. The

330 general pattern for the both the Central American region and the individual countries was for

331 certification to occur in cells with higher levels of conservation importance compared with non-

332 certified coffee-growing cells (Table 3). Rates of tree cover loss were lower in most cells with

333 certification, while the incidence of certification in cells with protected areas varied by country. In

334 Central America overall, certified cells tended to be closer to markets, while poverty levels in

335 certified cells were higher than in non-certified cells in Honduras and Nicaragua, and lower in

336 Mexico. Certified cells consistently occupied regions of higher altitude, slope and crop cover,

337 perhaps due to greater suitability of these conditions for high-quality shade-grown coffee, which is

338 more likely than sun-grown coffee to be marketed as a premium product to consumers for whom

339 certification has resonance.

340 *Case study: Oil Palm in Southeast Asia*

341 Certified oil palm in Southeast Asia (SE Asia) was found solely in Malaysia and Indonesia and tended

342 to be located in grid cells with lower than average importance for bird conservation than non-

343 certified oil palm and in areas with lower coverage of IBAs and protected areas (Table 4). Rates of

344 tree cover loss were higher in certified cells in SE Asia. From a livelihoods perspective, certified cells

345 were closer to towns and had lower levels of poverty. Cells with certified oil palm were also in areas

346 with lower altitudes and slope and higher percentage of crop cover, suggesting that these might be

347 more favourable crop-growing areas. Patterns at the SE Asia regional level appeared primarily

348 influenced by patterns of certification in Malaysia. Certified oil palm cells in Indonesia appeared to

349 have few differences compared with non-certified cells, although they were perhaps located in more

350 favourable, intensively-farmed agricultural areas, as altitude and slopes were lower but field size and

351 percentage crop cover were higher.

352   Full graphical results for all crops and countries are available in the Supplementary Materials along

353   with additional crop by region case studies.

354

355   **Discussion**

356   We developed the most detailed global map of commodity crop certification yet produced. It shows

357   that certification for each crop is concentrated in certain geographical areas, and largely absent from

358   others (Fig. 1). According to available spatial data, most commodity crop certification is in tropical

359   countries, although this is a pattern that would change if spatial data were available for organic

360   schemes (Tayleur et al., 2016). Our analysis quantified biases in each crop's certified locations

361   compared with gradients of conservation importance, tree cover loss and poverty (Table 1). Patterns

362   varied on a crop-by-crop and country-by-country basis, but overall, certification appears to be

363   concentrated in areas that are important for biodiversity conservation, relatively close to markets,

364   and with lower poverty levels (Figs 2, 3; Tables 1-4). These patterns suggest that existing standards

365   may be well-positioned to have a conservation impact if they promote the right practices, but are

366   less well-positioned to assist the very poorest farmers. However, there were exceptions to each of

367   these patterns, and relationships between certification and other variables were less consistent

368   (Tables 1-4). Some of the patterns found when data were pooled at global or regional levels persist

369   within individual countries, while others do not (Tables 2-4). This underlines the importance of

370   selecting the most appropriate decision-relevant scale for analysis of spatial patterns.

371   *Explaining patterns of certification*

372   Some of the patterns likely reflect geographical differences in growing practices, some of which are

373   more amenable to certification than others. For example, shade-grown coffee is more likely to meet

374   requirements of speciality coffee buyers and many certification standards, and growers may be

375   more likely to seek certification, compared with sun-grown coffee (Takahashi and Todo, 2014). The

376   higher conservation value of certified coffee cells in Central America might be because shade-grown

377 coffee, and thus certified coffee, is more common in remote, high altitude locations with steep

378 slopes (Table 3): locations where many restricted-range species could be expected to occur. Other

379 patterns are more difficult to explain, such as higher rates of tree cover loss in cells with certified

380 cocoa, palm oil, and soy. In the case of palm oil and soy especially, halting deforestation is a key

381 objective for certification standards. It may be that certification is reaching these crops in recent

382 frontiers, while being associated with more established areas of cultivation for other crops, such as

383 tea and coffee. If land at high risk from forest clearance is becoming certified, this could be good

384 news for conservation, as long as certification proves effective at preventing deforestation (e.g.

385 Rueda et al., 2014). Another possible interpretation is that this pattern reflects a failure by standards

386 to prevent deforestation, either because the deforestation occurred prior to certification; because of

387 incomplete certification coverage within the landscape; or because of weaknesses in the standards

388 and their application (e.g. Jurjonas et al., 2016; Tejeda-Cruz et al., 2010). Many standards do not

389 exclude all deforestation, and protect only primary forest or areas of High Conservation Value

390 (Edwards and Laurance, 2012; Tayleur et al., 2016). A third explanation for the global pattern, at

391 least in the case of soy, is the fact that certification has concentrated in some countries (e.g. Brazil)

392 and not others (e.g. the United States). An improvement in the quality of the spatial data, including

393 accurate farm boundaries, would allow the relative importance of these different explanations to be

394 explored in more detail.

395 Lower levels of certification in grid cells with the highest poverty rates and that are most isolated

396 from markets might be the result of certification having focused on highly exported commodities

397 (Tayleur et al., 2016) where supply chains are highly organized and exporters encourage or require

398 certification (Getz and Shreck, 2006; Neilson, 2008; Vellema et al., 2015). Certification has been

399 criticized as having high barriers to entry for smallholders (e.g. Brandi et al., 2015) although

400 increasing efforts are being made to include smallholders (Fernando et al., 2015), and there is some

401 evidence of social benefits (Hendriksen and Tholen, 2013). Certified farmers may also be those who

402 are wealthier and more educated, and therefore better able to meet certification requirements and

403 costs. Alternatively, the pattern might indicate that certification has already contributed to reducing

404 poverty in some areas (e.g. Rueda and Lambin, 2013) although many studies have failed to

405 demonstrate economic benefits (e.g. Ibanez and Blackman, 2016; Vellema et al., 2015). Finally, the

406 failure of some standards to reach the very poorest areas might be explained by a greater focus on

407 environmental rather than social criteria. Disentangling these contrasting explanations, using more

408 precise spatial data, and longitudinal environmental and socio-economic data, would help to inform

409 efforts to improve rural livelihoods through certification. Our analysis is just a first step towards

410 understanding patterns of certification, and how it might be leveraged to improve agricultural

411 sustainability.

412 *Strengthen, consolidate or expand?*

413 Certification bodies, and other organizations that use and promote their sustainability standards,

414 have several strategic (and not mutually exclusive) options by which they can increase their impact:

415 1) improving standards on farms that are already certified; 2) consolidating efforts by certifying a

416 higher proportion of farms in landscapes where they are already active, and 3) expanding

417 certification into new areas. Mapping the coincidence of certified locations with environmental and

418 social variables can help to prioritize these actions. We discuss opportunities for each of these three

419 strategies in detail.

420 To improve standards on certified farms, for example, it might be worthwhile for coffee certification

421 standards to incorporate stronger protection for wild species and their habitats in landscapes

422 identified as having especially high importance for conservation, such as those in Honduras (Table 3).

423 This could be achieved by incentivising farmers to 'step up' from entry-level schemes, such as the 4C

424 coffee standard, to more comprehensive standards, such as Rainforest Alliance/SAN. It could be

425 fostered by varying scheme requirements geographically, demanding compliance with key

426 biodiversity criteria in relevant areas or by ensuring more frequent or more thorough audits of

427 practices relevant to biodiversity. Audit data, in combination with spatial biodiversity data, could be

428   used to identify as high priorities for intervention any farms that are performing poorly against

429   environmental criteria in areas of conservation importance; the same analyses could be used to

430   reward farmers performing well in priority areas. Training programmes aimed, for instance, at

431   reducing specific threats such as hunting, or at habitat management for threatened species, could be

432   targeted towards producers in areas identified as being of especially high value for biodiversity

433   conservation. There might be specific opportunities for NGOs to engage with producers: for

434   example, certified tea in Kenya, and certified bananas in Costa Rica coincide with cells containing

435   IBAs (supplementary materials) suggesting an opportunity for bird conservation organizations to

436   work with certification organizations and certified farmers to improve conservation in these

437   locations.

438   Second, consolidation might be a good strategy in landscapes where certification already occurs in

439   areas with specific issues that it can help to address. For example, consolidating the coverage of

440   soybean-growing areas by standards that have effective criteria for avoiding deforestation could

441   help address this issue, as soybean certification is already taking place in landscapes with high levels

442   of tree cover loss. Consolidation could be facilitated by certification bodies taking a broad-scale

443   landscape approach as advocated by Tscharntke et al. (2015) whereby conservation outcomes are

444   promoted at a scale greater than farm level. Consolidation could also be supported by third parties

445   such as governments or NGOs, if they set requirements for adoption of certified practices, or

446   provide technical assistance to encourage their uptake. One example of this 'jurisdictional' approach

447   is being promoted by the RSPO and local government in Central Kalimantan (Nepstad et al., 2013;

448   RSPO, 2015).

449   Third, expanding certification into new areas would be most useful in cases where certification is

450   currently missing the areas of highest priority for specific issues, where voluntary standards are

451   more rigorous than legislation (Garrett et al., 2016), and where there is good reason to expect

452   positive impacts of standards. Certification of oil palm in Malaysia, for example, appears not to reach

453   the oil-palm-growing areas where poverty levels are highest, perhaps because it is unattractive or

454   inaccessible to smallholders (Reitberg and Slingerland, 2016). Schemes could reduce social and

455   economic obstacles to uptake in poorer regions by providing targeted training, support for producer

456   cooperatives, and policies that simplify requirements and reduce certification fees for smallholders.

457   The RSPO is adopting some of these approaches in an attempt to increase smallholder uptake.

458   Comparing regional with country-level patterns of importance for birds and mammals suggests that

459   certification in West and Central Africa misses some of those cocoa-growing areas that are most

460   important for biodiversity. Extending certification to cocoa-growing countries it has barely reached,

461   such as Sierra Leone and Togo, while strengthening biodiversity-related criteria, could play a role in

462   conservation efforts. However, expansion would need to be linked to an appropriate market,

463   because while some certified products such as coffee and cocoa now have mainstream markets –

464   40% and 22% of production respectively – demand has tended to lag supply. For example, less than

465   one third of certified coffee was sold as such in 2012, which may limit future expansion and financial

466   benefits for farmers (Potts et al., 2014). Efforts to expand certification can also go further to

467   consider crops which have been neglected. One point of entry would be for food companies to

468   expand certification requirements to all ingredients in their supply chains, including those such as

469   rice, maize and livestock products which have been poorly covered by standards (Newton et al.,

470   2015; Tayleur et al., 2016).

471   *Key data challenges and limitations*

472   The accuracy of our analyses was limited by data quality. Many schemes have not yet developed

473   rigorous protocols for the collection and/or sharing of spatial data. As a result, spatial data were

474   often available for only a subset of the certificates within each standard. For some standards, no

475   spatial data were available. For example, we contacted more than 200 organizations that certify

476   organic agriculture, but received few positive responses covering only a handful of producers. For

477   some crops (cotton, and in some cases sugarcane) certification locations referred to processing mills,

478   not to farms. Other schemes were only able to provide addresses. The use of non-standard address

479   formats and non-Roman alphabets meant that the success rate of geocoding was low and those

480   coordinates that were created could not be ground-truthed. For our analysis we summarized data at

481   the 30-km scale. This was primarily to ensure farmer confidentiality, but also reduced the impact of

482   imprecise spatial coordinates and farms with multiple certifications. A disadvantage of aggregation

483   at this scale is that a large proportion of land within each cell is likely not certified. Our decision to

484   use the Monfreda map, clipped with the GAEZ map, was also an imperfect representation of crop

485   distribution for our 'control' distributions, but these were the best global data available. Finer-

486   resolution analyses would be preferable in order to reflect the true spatial patterns for individual

487   standards. It is important to recognize that our analyses show only correlation, and not causation,

488   but correlations are useful for identifying gaps and priorities.

489   Our difficulties in locating and assembling a spatial database of certification lead us to recommend

490   that greater resources be invested by certification organizations in collecting and organizing such

491   information. While during the course of this study we found that spatial data were often lacking and

492   poorly curated, there is a growing awareness within the industry of its value (Mallet et al., 2016).

493   Improving the provision of spatial data is consistent with the commitments of certification

494   organizations to transparency and traceability. Challenges remain, such as ensuring that the right to

495   privacy of producers is respected, and that commercially-sensitive data are handled appropriately.

496   However, these challenges are surmountable, and putting certified producers on the map also has

497   several benefits. Transparency can be used to deflect criticism: for example, open RSPO data have

498   been used to show that most fires are not on RSPO concessions (http://www.rspo.org/news-and-

499   events/news/rspo-statement-on-the-indonesian-forest-fires). Good spatial data are essential for

500   demonstrating and auditing compliance with some criteria, such as adherence to restrictions on

501   deforestation (Tayleur and Phalan, 2016). Being able to cross-reference spatial data from different

502   standards could help to identify overlaps and streamline audit processes. Bodies such as the ISEAL

503   Alliance, which supports the sustainability standards community to define and implement best

504   practices, could request minimum transparency guidelines for membership, and define best practice

505   for spatial data management and dissemination.

506

507   **Conclusions**

508   Certification is an increasingly ubiquitous tool, promoted by both the private sector and civil society

509   as important for improving the conservation and socio-economic impacts of agriculture. Our global

510   data synthesis revealed a number of concentrations of certification, both geographically and also

511   with respect to gradients of biodiversity, tree cover loss and poverty. While certification appeared to

512   coincide with areas important for biodiversity, it showed less overlap with areas of greatest poverty.

513   These results suggest either a mismatch between the objectives of sustainability standards studied

514   here and their potential to achieve them, or a greater emphasis on environmental than social

515   sustainability. Regional and country-level crop-specific analyses demonstrated different spatial

516   patterns, highlighting specific opportunities for increasing the impact of standards.

517   We describe three types of activities that could be targeted using spatial analyses to improve the

518   outcomes of certification: strengthening standards on certified farms, consolidating the coverage of

519   farms in already-certified landscapes, and expanding certification into new priority areas. As a

520   market-driven mechanism, certification will require support from a range of actors in the private and

521   public sector to enable spatial targeting. This would require private companies to consider

522   alternative and potentially riskier sourcing locations, financial institutions to strengthen the

523   environmental and social components of their lending criteria, NGOs to effectively advocate for

524   those areas that would benefit most and, finally, governments to provide favourable conditions and

525   requirements for sustainable production and trade. Better targeting in future would also be

526   facilitated by improved collection of spatial data, benchmarking across standards, and a renewed

527   commitment to transparency.

528

Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version. The dataset
underlying this analysis can be viewed in the Biological Conservation map viewer.

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701

Crop	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
	Importance for birds	Importance for amphibians	Importance for mammals	% Protected Area coverage	% IBA coverage	Rate of net tree cover loss	Field size	Travel time to market	% of population in poverty	Altitude	Slope	% crop cover
Coffee 1299/14397	Higher <0.0001	ns	Higher 0.0102	Lower 0.0200	ns	Lower <0.0001	Higher <0.0001	Lower <0.0001	Lower <0.0001	Higher <0.0001	Higher <0.0001	Higher 0.0032
Banana 50/14159	ns	ns	ns	ns	ns	ns	Higher <0.0001	Lower 0.0207	Lower <0.0001	ns	Higher 0.0160	Lower 0.0202
Soy 66/28179	ns	Lower 0.0075	ns	ns	ns	Higher <0.0001	Higher <0.0001	Higher <0.0001	Higher 0.0003	ns	ns	Lower <0.0001
Tea 104/5164	Higher <0.0001	Higher 0.0024	ns	Higher 0.0010	Higher 0.0001	Lower 0.0003	Higher 0.0175	ns	ns	Higher <0.0001	ns	Higher <0.0001
Oil Palm 145/6631	ns	ns	ns	Lower 0.0027	ns	Higher <0.0001	Higher <0.0001	ns	Lower 0.0121	Lower <0.0001	Lower <0.0001	ns
Cocoa 202/8087	Higher 0.0247	ns	ns	Ns	Lower 0.019	Higher 0.0020	Lower <0.0001	Lower 0.0001	Lower 0.0016	ns	Higher 0.0245	Lower <0.0001
Sugar 110/19339	ns	ns	ns	ns	ns	ns	Higher <0.0001	Lower 0.0065	ns	Higher 0.0007	ns	Higher 0.0001

Table 1 Results from bootstrap resampling tests comparing the distribution of certified grid cells with non-certified crop growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.

Crop Cocoa	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
	Importance for birds	Importance for amphibians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of population in poverty	Altitude	Slope	% crop cover
West Africa 109/929	ns	ns	Higher 0.0001	ns	ns	Higher <0.0001	ns	Lower <0.0001	Lower 0.0037	Lower 0.0007	ns	Lower <0.0001
Ghana 26/127	Higher <0.0001	Higher <0.0001	ns	ns	Lower 0.0066	ns	Lower <0.0001	Lower 0.0023	ns	ns	Higher 0.0190	Lower <0.0001
Cameroon 8/170	Higher <0.0001	ns	Higher <0.0001	ns	ns	ns	Lower <0.0001	Lower 0.0163	ns	ns	Higher 0.0171	Lower 0.0199
Côte d'Ivoire 65/225	Higher <0.0001	Higher 0.0005	Higher 0.000	ns	ns	Higher <0.0001	ns	Lower <0.0001	Lower <0.0001	Lower <0.0001	Lower 0.0023	Lower <0.0001
Nigeria 7/180	ns	Higher 0.0008	Higher 0.0188	ns	ns	ns	ns	ns	ns	ns	ns	ns

Table 2 Results from bootstrap resampling tests comparing the distribution of certified cocoa grid cells versus non-certified cocoa growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.

Crop Coffee	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
	Importance for birds	Importance for amphibians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of population in poverty	Altitude	Slope	% crop cover
Central America 191/627	Higher <0.0001	Higher 0.0040	Higher <0.0001	Higher 0.0166	N/A	Lower <0.0001	ns	Lower <0.0001	ns	Higher <0.0001	Higher <0.0001	Higher <0.0001
Honduras 39/89	ns	Higher <0.0001	Higher <0.0001	Lower <0.0001	N/A	Lower <0.0001	Higher <0.0001	Lower <0.0001	Higher <0.0001	Higher <0.0001	Higher <0.0001	Higher <0.0001
Mexico 47/299	ns	ns	Higher <0.0001	Higher 0.0002	N/A	ns	ns	ns	Lower 0.0139	Higher 0.0017	ns	Higher <0.0001
Nicaragua 29/74	Higher 0.0002	Higher <0.0001	Higher <0.0001	Lower <0.0001	Lower <0.0001	Lower <0.0001	Lower <0.0001	Lower <0.0001	Higher 0.0098	Higher <0.0001	Higher <0.0001	Higher <0.0001

Table 3 Results from bootstrap resampling tests comparing the distribution of certified coffee grid cells versus non-certified coffee growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name. We did not have spatial data on IBAs in Mexico or Honduras, hence the N/As in the IBA column.

Crop Oil Palm	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
	Importance for birds	Importance for amphibians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of population in poverty	Altitude	Slope	% crop cover
SE Asia 109/1728	Lower <0.0001	ns	ns	Lower 0.0076	Lower 0.0054	Higher 0.0022	ns	Lower <0.0001	Lower <0.0001	Lower <0.0001	Lower <0.0001	Higher <0.0001
Malaysia 51/196	Lower <0.0001	ns	Higher 0.0014	Lower 0.0151	Lower 0.0036	Higher 0.0039	ns	Lower <0.0001	Lower <0.0001	Lower <0.0001	Lower <0.0001	Higher <0.0001
Indonesia 58/1212	Lower 0.0002	ns	ns	ns	ns	ns	Higher 0.0141	ns	ns	Lower <0.0001	Lower <0.0001	Higher <0.0001

Table 4 Results from bootstrap resampling tests comparing the distribution of certified oil palm grid cells versus non-certified oil palm growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.
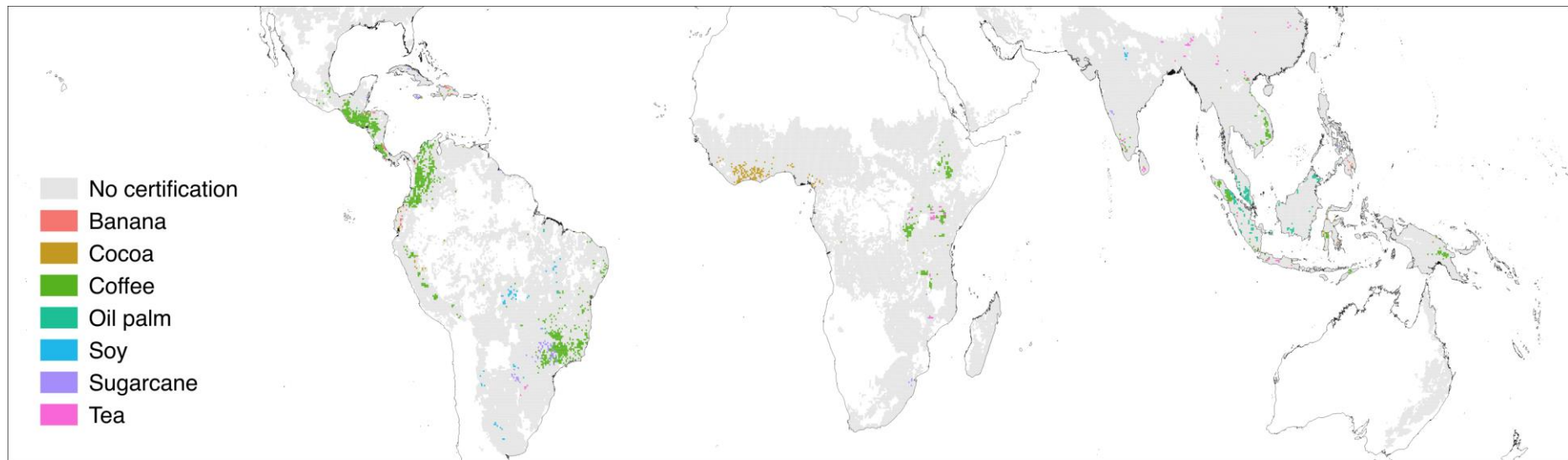
Figure 1 Global distribution of certified commodity crops based on their presence within 30 km × 30 km grid cells. Colours indicate the crop with the most certificates in each grid cell. The combined distribution of the named crops, from Monfreda et al. (2008), is shown in pale grey, and the map is cropped to the distribution of certificates with spatial data, which were predominantly in the tropics. Map produced using QGIS 2.18.2 (QGIS Development Team, 2017). An interactive version of these data is available in the online article.
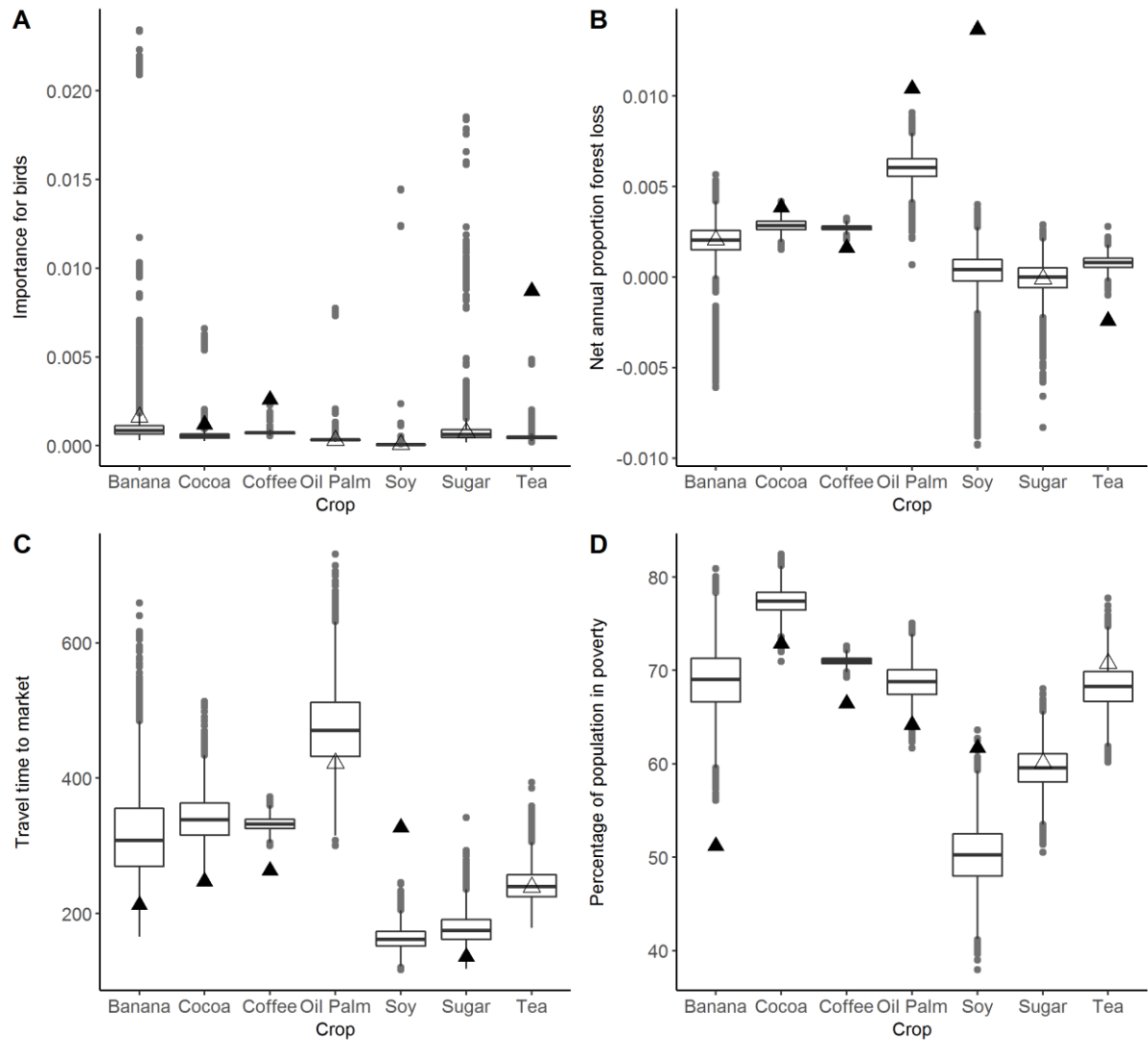
Figure 2. The distribution of values for a selection of variables across their global crop-growing range, shown using box plots. The value for certified grid cells is signified by either an open triangle where the value was not significantly different from the global distribution, or a solid triangle when it was significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
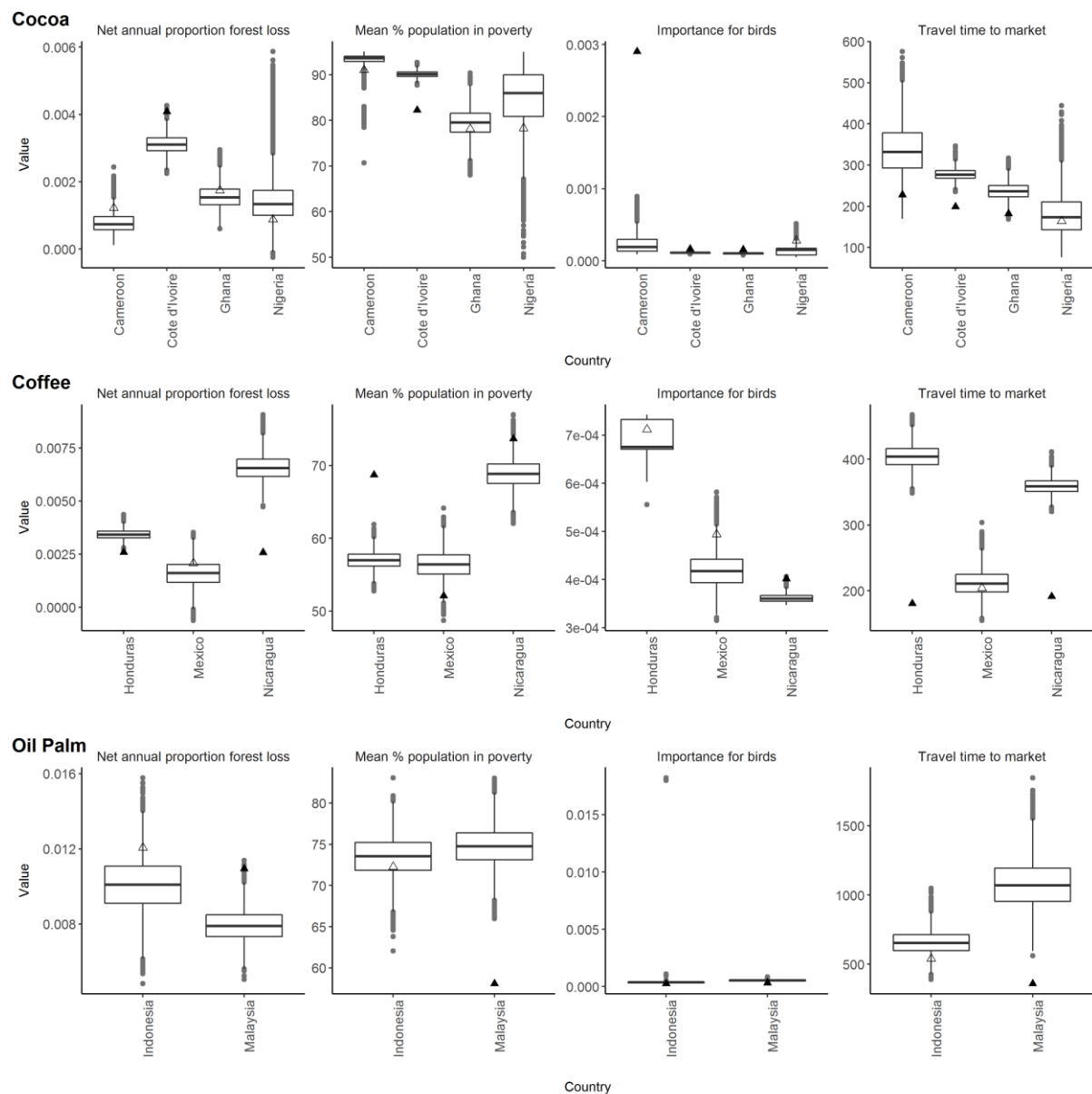
Figure 3. The distribution of values for a selection of variables across their crop-growing range within selected countries shown using box plots. The value for certified grid cells is signified by either an open triangle where the value was not significantly different from the global distribution, or a solid triangle when it was significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.

Where are commodity crops certified, and what does it mean for conservation and poverty alleviation?

Supplementary Materials:

Materials and Methods:

Data

Certification data

We compiled information on the specific location of certified producers, certified area, and crops certified. We aimed to collect information for all sustainability standards that cover agricultural commodities that are listed in the State of the Sustainability Initiatives report from 2012 (Potts et al., 2014). We also included the Starbucks C.A.F.E practices and Bird-friendly coffee schemes due to their similarity to other coffee certification initiatives, and Etanol Verde as a relatively new biofuel certification scheme. Attempts to obtain data from GLOBAL G.A.P and Proterra were not successful, while the Better Cotton Initiative (BCI) did not hold appropriate spatial data. We contacted approximately 120 organisations that are involved with organic certification, including all of those listed as sources of organic data in (Willer and Kilcher, 2012). Only two of these organizations were able to provide appropriate data so we decided to exclude organic certification from our analysis. A list of all other schemes included and the sources for the data are provided below. We did not restrict the scope of our search for data to a particular geography. However, with the exception of organic certification, existing certification schemes are predominately restricted to tropical countries.

Most data were provided under condition that individual farmer locations and the locations of individual schemes were not identifiable. Therefore all data were summarized and anonymized using 30 km × 30 km grid cells.

4C

Data were provided directly by 4C in June 2014 the form of addresses in excel spreadsheets. Sites that did not report hectares under coffee plantation were excluded as well as any certified entities that were not coffee growers. After data processing we were left with 269606 individual addresses. Areas were summed for the same address. The data were geocoded using the World Geocode Service in ArcMap 10.2. We were able to obtain coordinates for 60815 sites that also coincided with coffee growing regions.

Bird-friendly coffee

https://www.google.com/fusiontables/DataSource?docid=15r1LIYRX-CwbK7Xa0L-i1xU5sLBy2_Y_U6_MHDg#rows:id=1 Accessed 16/04/2014

Bonsucro

http://bonsucro.com/site/certification-process/certified-members/ Accessed 15/04/2014

Individual sites were located using a google maps search where sugar mills were identified by eye.

Etanol Verde

Data obtained from http://www.unica.com.br/ Accessed 29/04/2014
Certificates from 2013 were included. Sites located using a google maps search where sugar mills were identified by eye.

Fairtrade

Data were provided directly by FLO-CERT in the form of coordinates, on the 17th September 2014.

Florverde

Data were provided directly by Florverde in the form of coordinates on 1st July 2014. These data were not included in the final analysis as they were for cut flowers.

ISCC

http://www.iscc-system.org/en/certificate-holders/valid-certificates/ Accessed 30/01/2015

Rainforest Alliance

Data were provided directly by Rainforest Alliance in September 2014 the form of coordinates.

Roundtable Responsible Soy (RTRS)

Data were obtained from WWF in November 2013 in the form of coordinates. Only sites that had certificates still valid in 2013 were included.

Roundtable on Sustainable Biomaterials (RSB)

http://rsb.org/certification/participating-operators/ Accessed 22/04/2014
 Only those certified to grow crops were included.

Roundtable on Sustainable Palm Oil (RSPO)

Data for RSPO certified sites were originally available to view on their website http://www.rspo.org/ Accessed 16/04/2014. Presence of RSPO palm oil was established by cross-referencing the RSPO certified map with our 30km grid. If a single plantation overlapped with more than one grid cell then all were classified as containing certified palm oil.

Starbucks C.A.F.E. Practices

Data were obtained from Starbucks directly in the form of coordinates on 30th January 2015.

UTZ

Data were provided directly by UTZ in the form of coordinates on 28th July 2014.

Regional and country level analyses
Regional grouping of countries were used to examine patterns of certification in several 'hotspots'. These were:
West and Central Africa cocoa growing countries

Cameroon, Congo Cote d'Ivoire, Equatorial Guinea, Gabon, Ghana, Guinea, Nigeria and Sierra Leone.

Central American coffee growing countries

Belize, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua and Panama.
Panama had no certified cells. Please note that in Costa Rica, Guatemala and El Salvador the number of certified grid cells exceeded non-certified cells so patterns in these countries were not examined. The number of certified to non-certified cells in these countries were: Costa Rica 20/32, El Salvador 9/10, Guatemala 47/88.

South-East Asian oil palm growing countries

Indonesia, Malaysia, Philippines and Thailand.

Additional results

Table S1: List of crops for which certified locations were provided along with the number of certificates. These totals are for the unvalidated data. Subsequent data validation and analysis were carried out for the seven most certified crops (banana, cocoa, coffee, oil palm, soy, sugarcane and tea). "Cane sugar", "Sugar & Ethanol", "Sugar mill" and "Sugarcane" were combined as sugarcane.

Crop	Number of certificates
Avocado	4
Banana	287
Blackberry	1
Buttercup squash	1
Cane sugar	68
Cardamom	1
Cassava	1
Cattle	3
Cherry	1
Chive	1
Cinnamon	1
Citrus	9
Clove	1
Cocoa	577
Coconut	1
Coffee	78087
Corn	3
Dried fruit	14
Durazno	1
Ethanol	3
Flowers	119
Flowers and Plants	59
Forest	300
Fresh fruit	87
Fruit juices	10
Grapes	37
Herbs	60
Honey	36
Kiwi	1
Lemon	1
Macadamia	3
Mango	2
Melon	1
Nutmeg	1
Nuts	39

Oil Palm	353
Oilseeds	40
Onion	1
Orange	1
Papaya	1
Paprika	1
Passion Fruit	1
Peach	1
Pepper	6
Pineapple	14
Pitajaya	1
Plantain	2
Pomegranate	1
Potato	20
Pulp	5
Pumpkin	2
Quinoa	7
Rice	20
Roselle / Hibiscus	1
Rubber	2
Seed cotton	22
Soy	4124
Stevia	1
Strawberry	1
Sugar & Ethanol	24
Sugar mill	64
Sugarcane	9
Tea	245
Vanilla	3
Vegetables	36
Walnut	1
Wine grapes	21
Yerba Mate	1
TOTAL	84853

Table S2 Results from bootstrap resampling tests comparing the distribution of certified tea grid cells versus non-certified tea growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.

Crop	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
Tea	Importance for birds	Importance for amphi-bians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of Population in poverty	Altitude	Slope	% Crop cover
Kenya 31/103	ns	ns	Higher <0.0001	ns	Higher 0.0238	Lower <0.0001	Higher 0.0144	Higher 0.0128	Lower <0.0001	ns	ns	Lower <0.0001
India 21/221	Higher 0.0212	Higher 0.0233	Higher 0.0245	ns	ns	Lower <0.0001	Lower 0.022	ns	ns	ns	ns	ns
China 10/1910	ns	ns	ns	ns	ns	ns	ns	ns	ns	ns	Higher 0.0041	Lower 0.0034
Indonesia 9/450	Higher 0.0074	ns	ns	ns	ns	Lower <0.0001	Lower 0.0035	Lower 0.0008	Lower <0.0001	ns	ns	Higher <0.0001

Table S3 Results from bootstrap resampling tests comparing the distribution of certified soy grid cells versus non-certified soy growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.

Crop	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
Soy	Importance for birds	Importance for amphi-bians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of Population in poverty	Altitude	Slope	% Crop cover
Argentina 13/1256	ns	ns	ns	ns	ns	Higher 0.0029	ns	ns	ns	ns	ns	ns
Brazil 40/3186	Lower <0.0001	Lower <0.0001	Lower 0.0124	ns	ns	Higher <0.0001	Higher <0.0001	Higher <0.0001	Lower <0.0001	Lower 0.0024	Lower <0.0001	Lower <0.0001

Table S4 Results from bootstrap resampling tests comparing the distribution of certified banana grid cells versus non-certified banana growing cells. Where the value for certified cells was significantly lower than for non-certified cells, the results are shown in light grey, while significantly higher certified values are shaded in dark grey. The values represent the significance value calculated as the number of non-certified values smaller or larger than the certified test statistic divided by the number of permutations (10,000). As tests were two-tailed, the significance threshold was set at 0.025. The fraction of certified to non-certified cells is given under the crop name.

Crop	Biodiversity and Environmental parameters						Livelihoods parameters			Physical parameters		
Banana	Importance for birds	Importance for amphi-bians	Importance for mammals	% Protected Area	% IBA	Rate of net tree cover loss	Field size	Travel time to market	% of Population in poverty	Altitude	Slope	% Crop cover
Ecuador 9/95	ns	ns	ns	ns	ns	ns	ns	ns	Lower 0.0069	ns	ns	ns
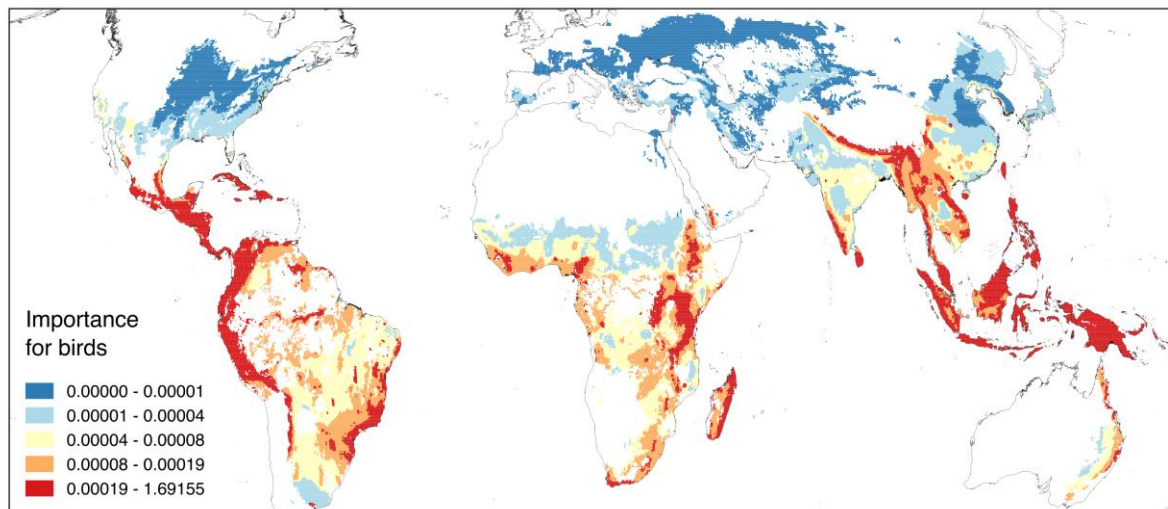
Fig. S1. Importance for birds across the combined distribution of the seven focal crops. Values indicate the summed proportions of all species' ranges that occur in a given 30 km × 30 km cell. Data: Birdlife International and NatureServe (2014).
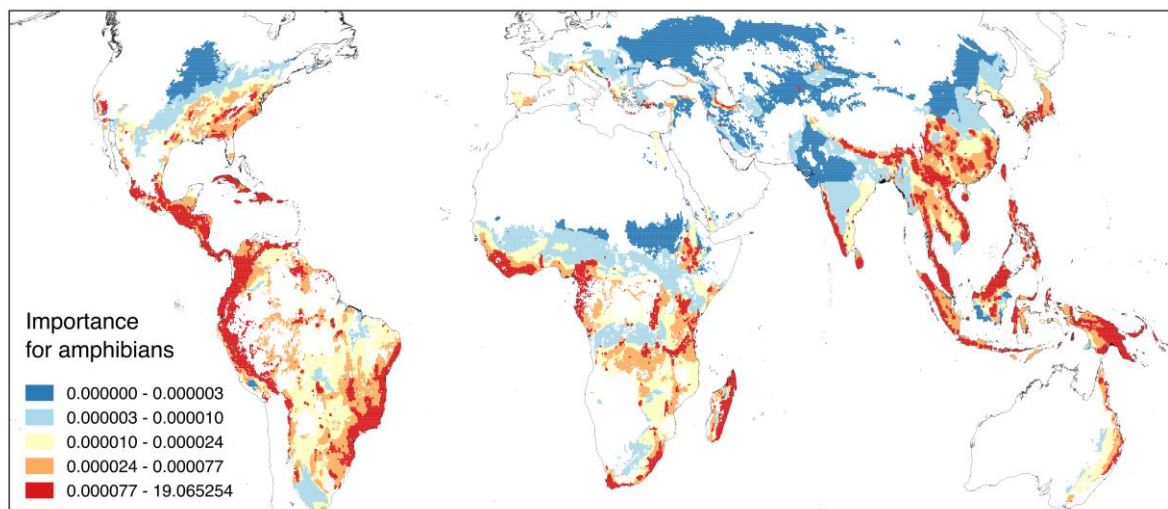
Fig. S2. Importance for amphibians across the combined distribution of the seven focal crops. The values indicate the summed proportions of all species' ranges that occur in a given 30 km × 30 km cell. Data: IUCN (2014).
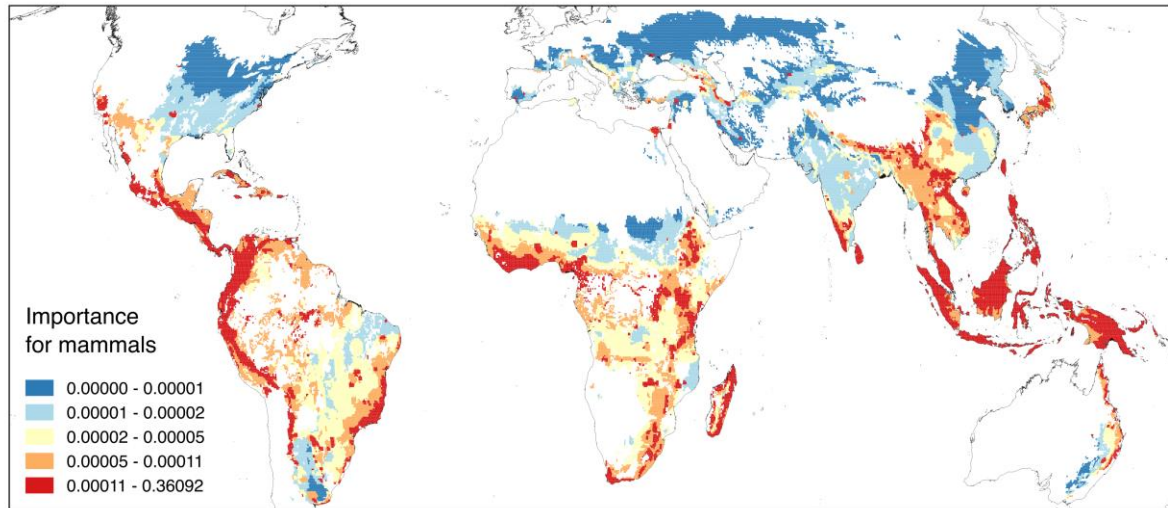
Fig. S3. Importance for mammals across the combined distribution of the seven focal crops. The values indicate the summed proportions of all species' ranges that occur in a given 30 km × 30 km cell. Data: IUCN (2014).
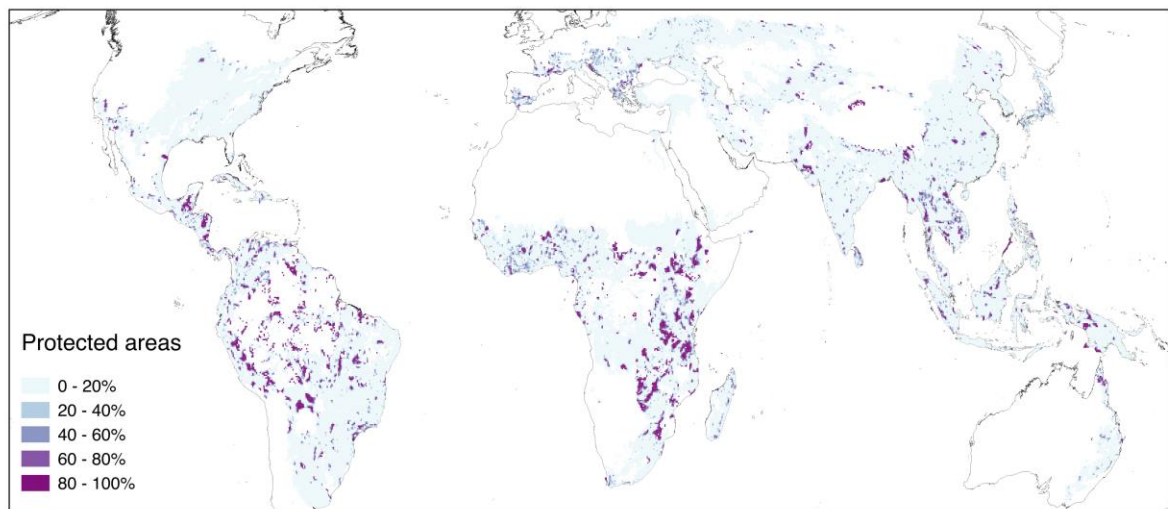
Fig. S4. Distribution of protected areas across the combined distribution of the seven focal crops, mapped as the percentage of land protected per 30 km × 30 km cell. Data: IUCN & UNEP-WCMC (2015).
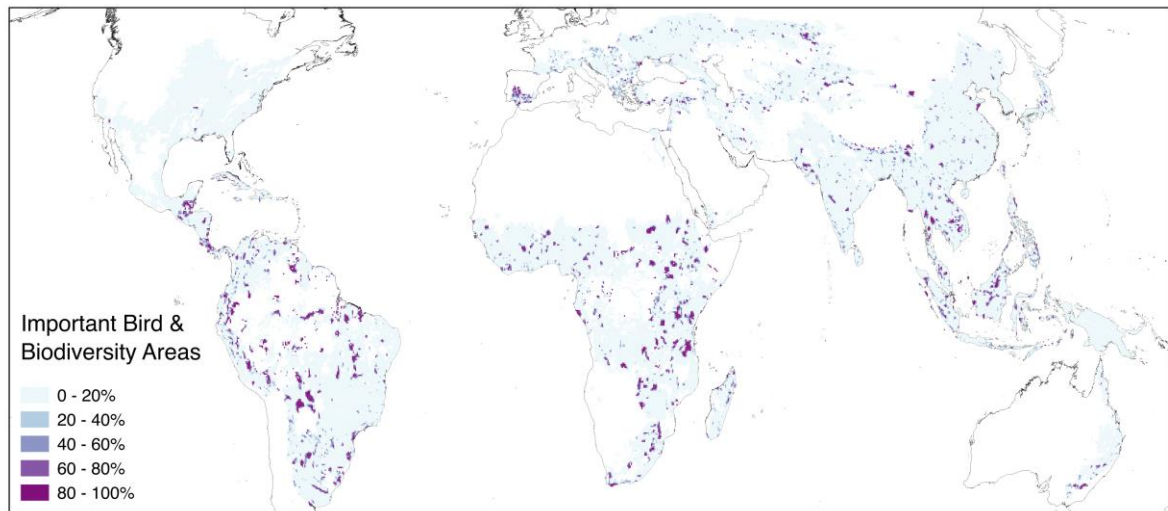
Fig. S5. Distribution of Important Bird and Biodiversity Areas across the combined distribution of the seven focal crops. Data: BirdLife International (2015).
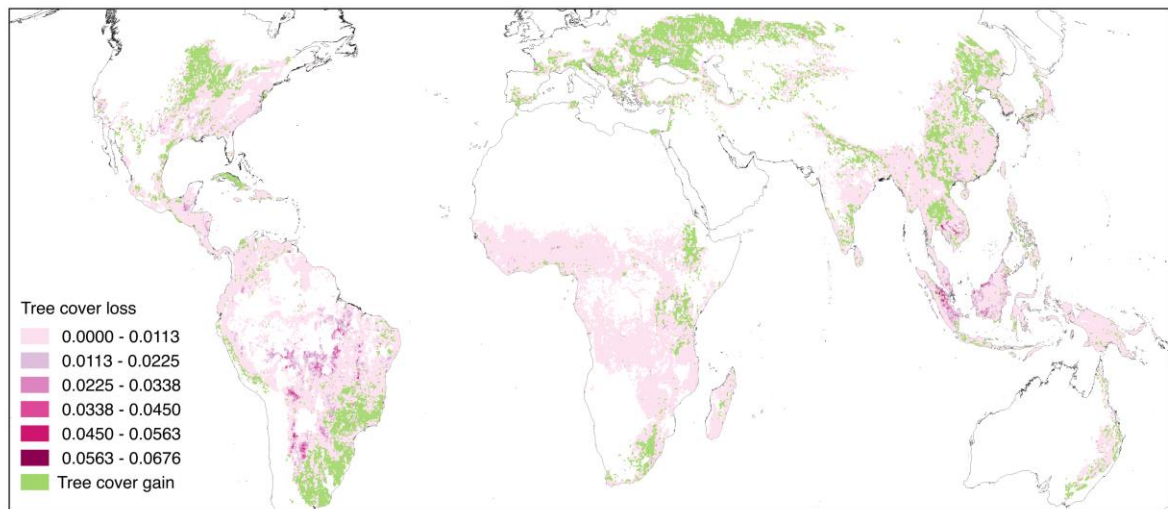
Fig. S6. Rate of net tree cover loss (pink) and gain (green) between 2000 and 2012, across the combined distribution of the seven focal crops, as a proportion of the original tree cover per 30×30 km cell, calculated from 30-m resolution data resampled to 200-m resolution. Data: Hansen et al. (2013) and Google Earth Engine Team (2015).
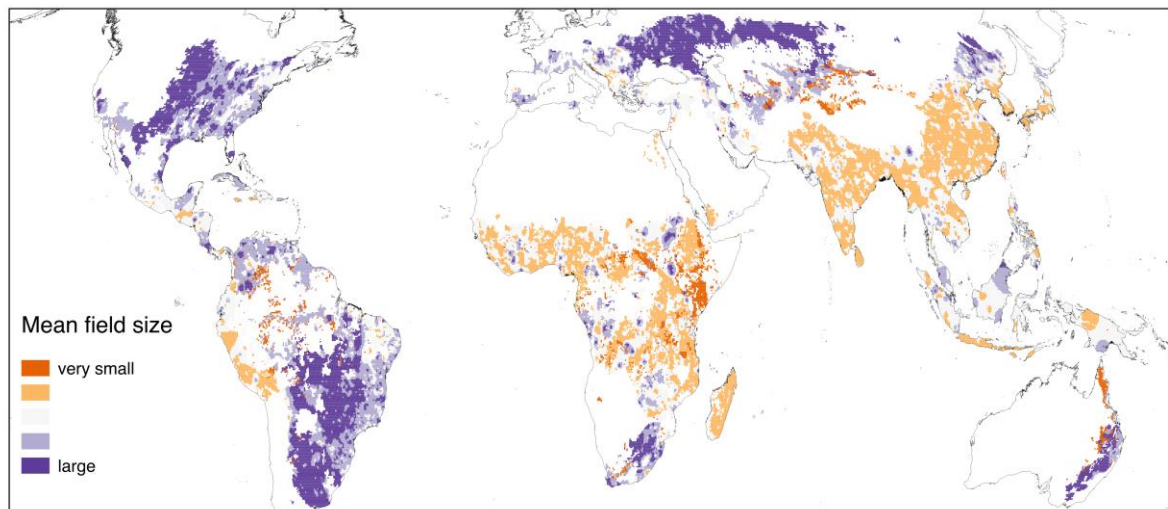
Fig. S7. Mean field size (from four-level scale: very small, small, medium, large) across the combined

distribution of the seven focal crops. Data: Fritz et al. (2015).
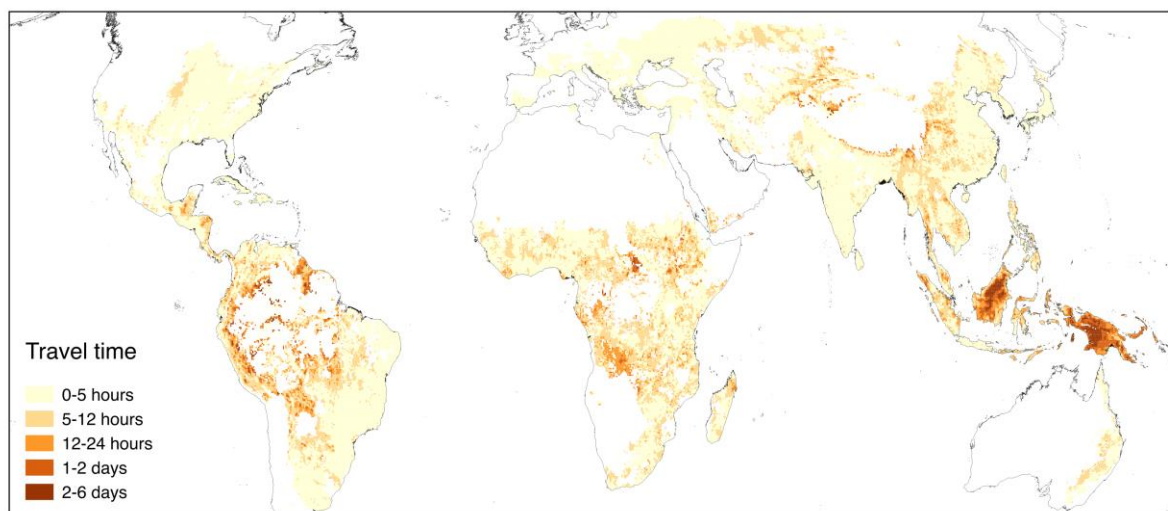
Fig. S8. Mean travel time to markets across the combined distribution of the seven focal crops. Data:

Nelson (2008).
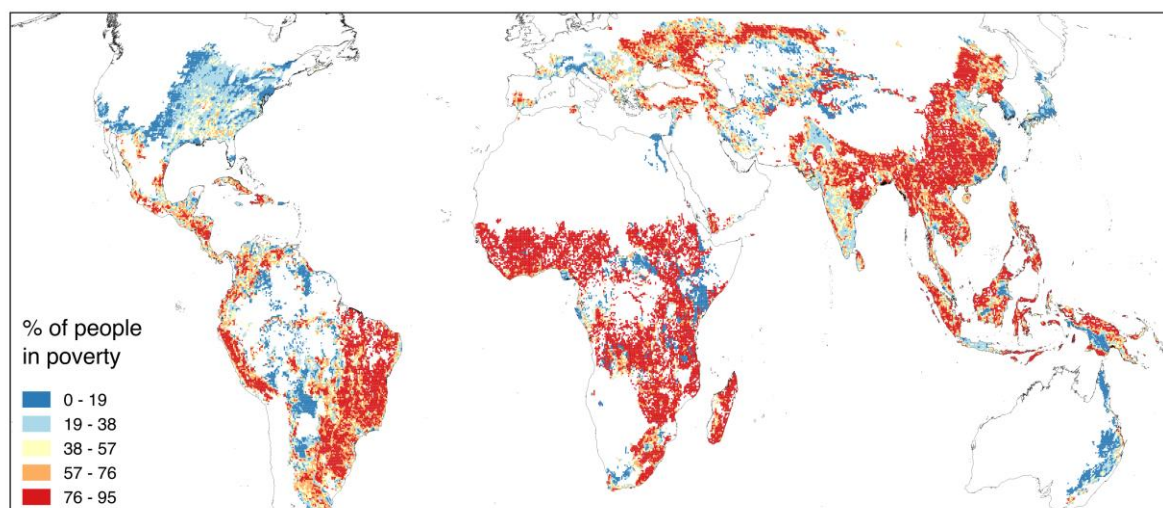
Fig. S9. Percentage of population in poverty across the combined distribution of the seven focal crops. Data: Elvidge et al. (2009).
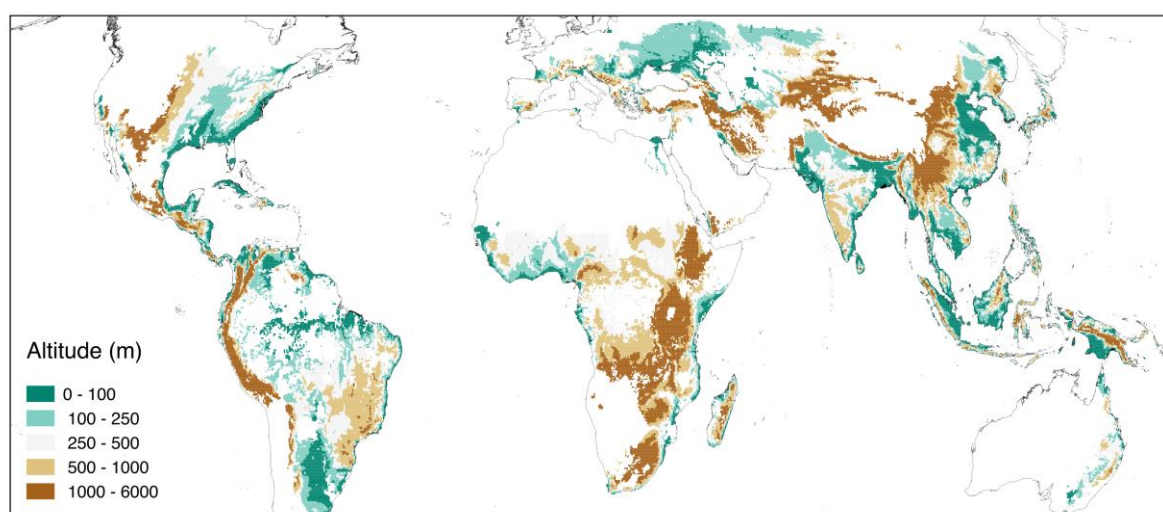
Fig. S10. Mean altitude across the combined distribution of the seven focal crops. Data: USGS (2004).
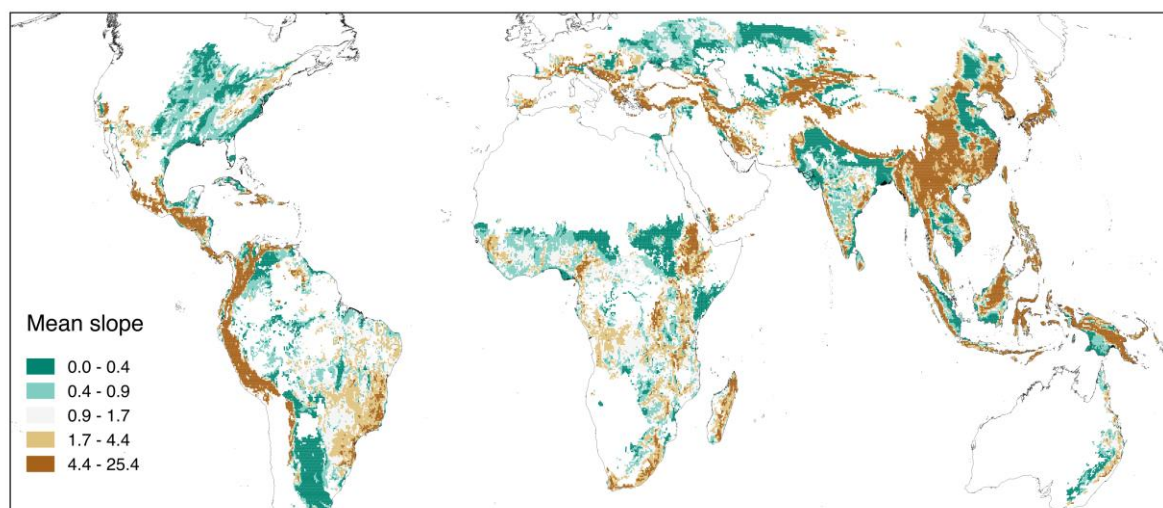
Fig. S11. Mean slope (degrees) across the combined distribution of the seven focal crops. Slope was calculated from 3 arc-second resolution SRTM data and averaged for each 30 km × 30 km cell. Data: USGS (2006).
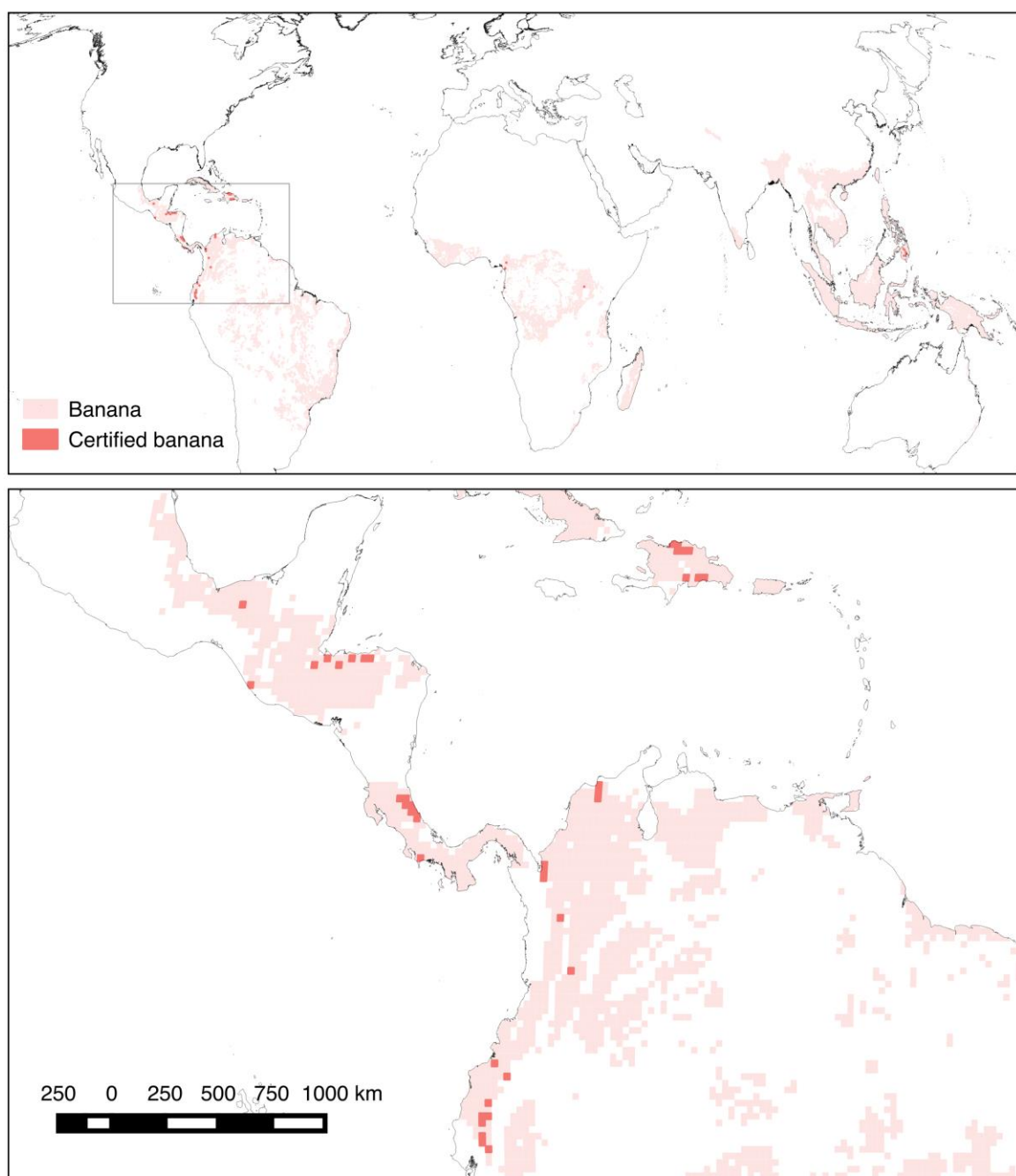
Fig. S12. Global distribution of banana, and of certified banana. Lower inset shows area with most certified banana (tropical Latin America) in more detail.
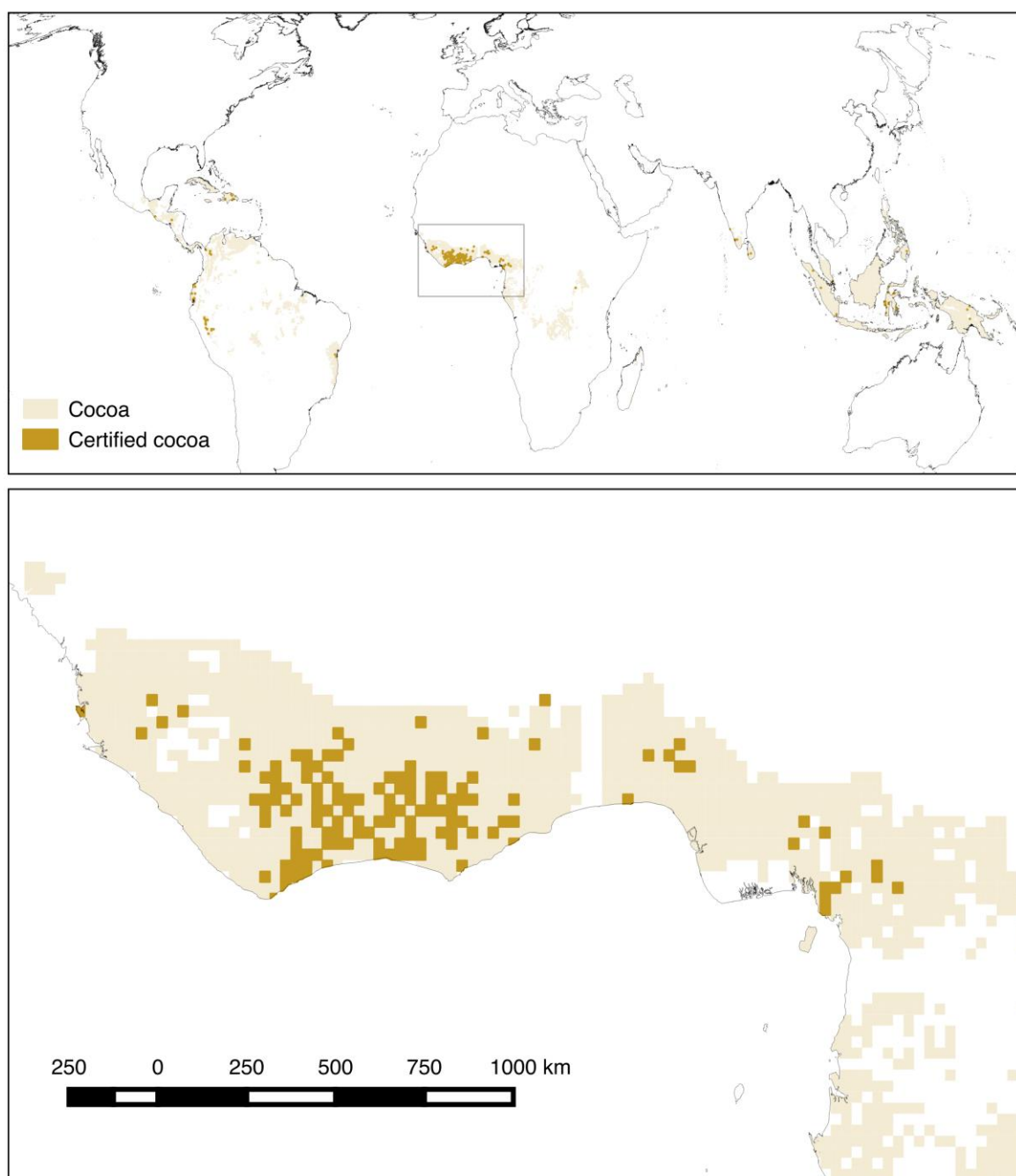
Fig. S13. Global distribution of cocoa, and of certified cocoa. Lower inset shows area with most certified cocoa (West Africa) in more detail.
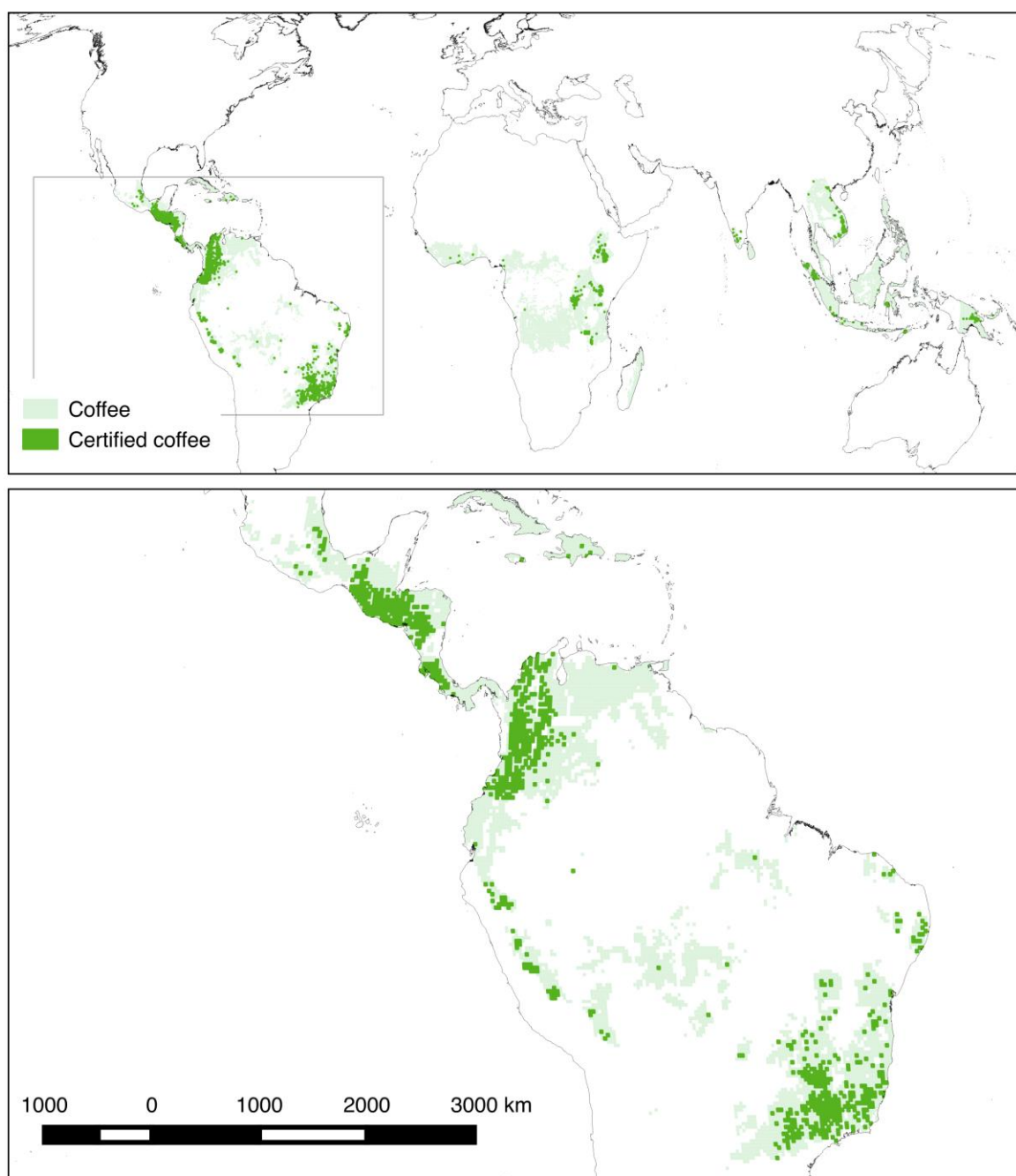
Fig. S14. Global distribution of coffee, and of certified coffee. Lower inset shows area with most certified coffee (Latin America) in more detail.
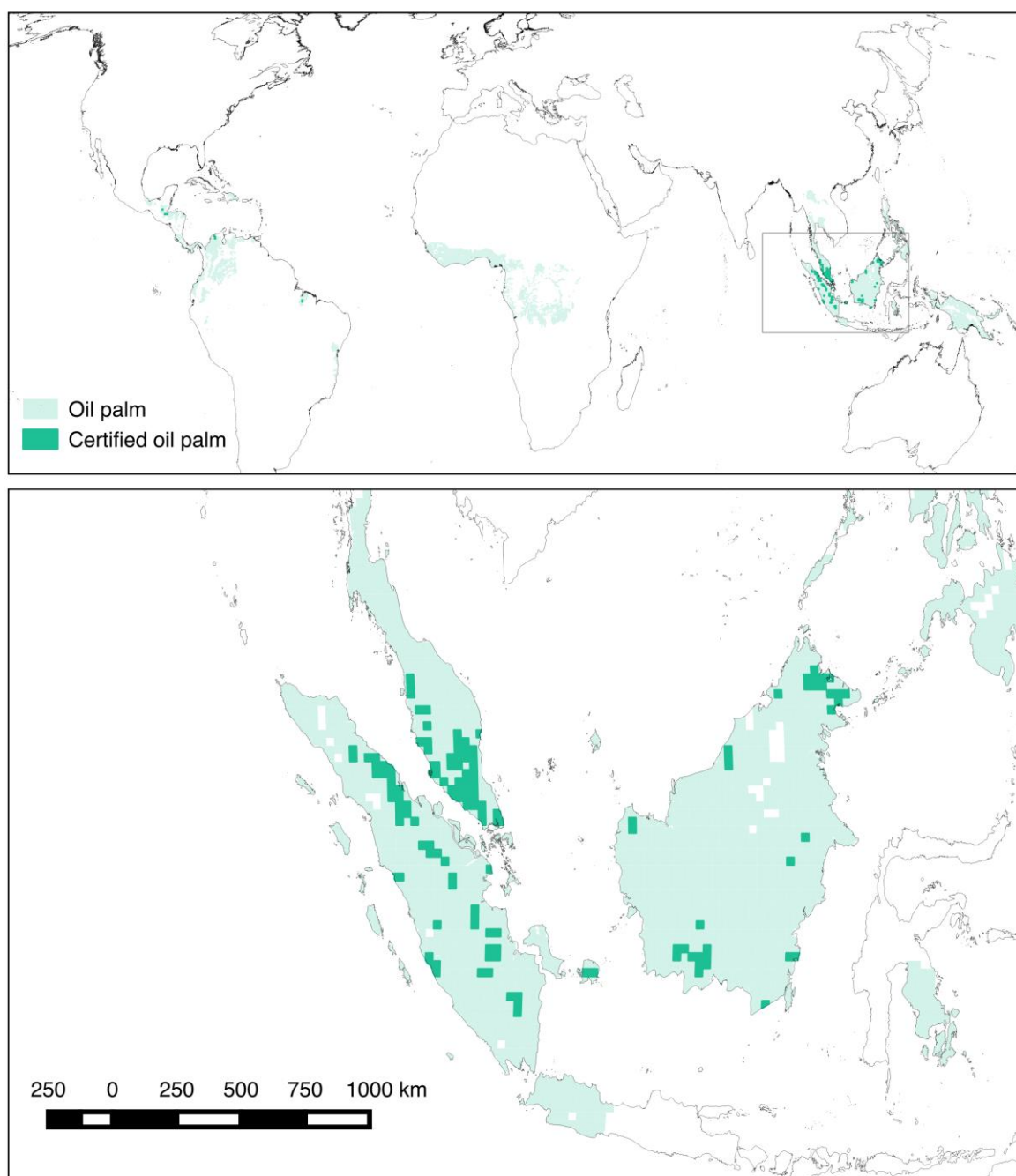
Fig. S15. Global distribution of oil palm, and of certified oil palm. Lower inset shows area with most certified oil palm (Southeast Asia) in more detail.
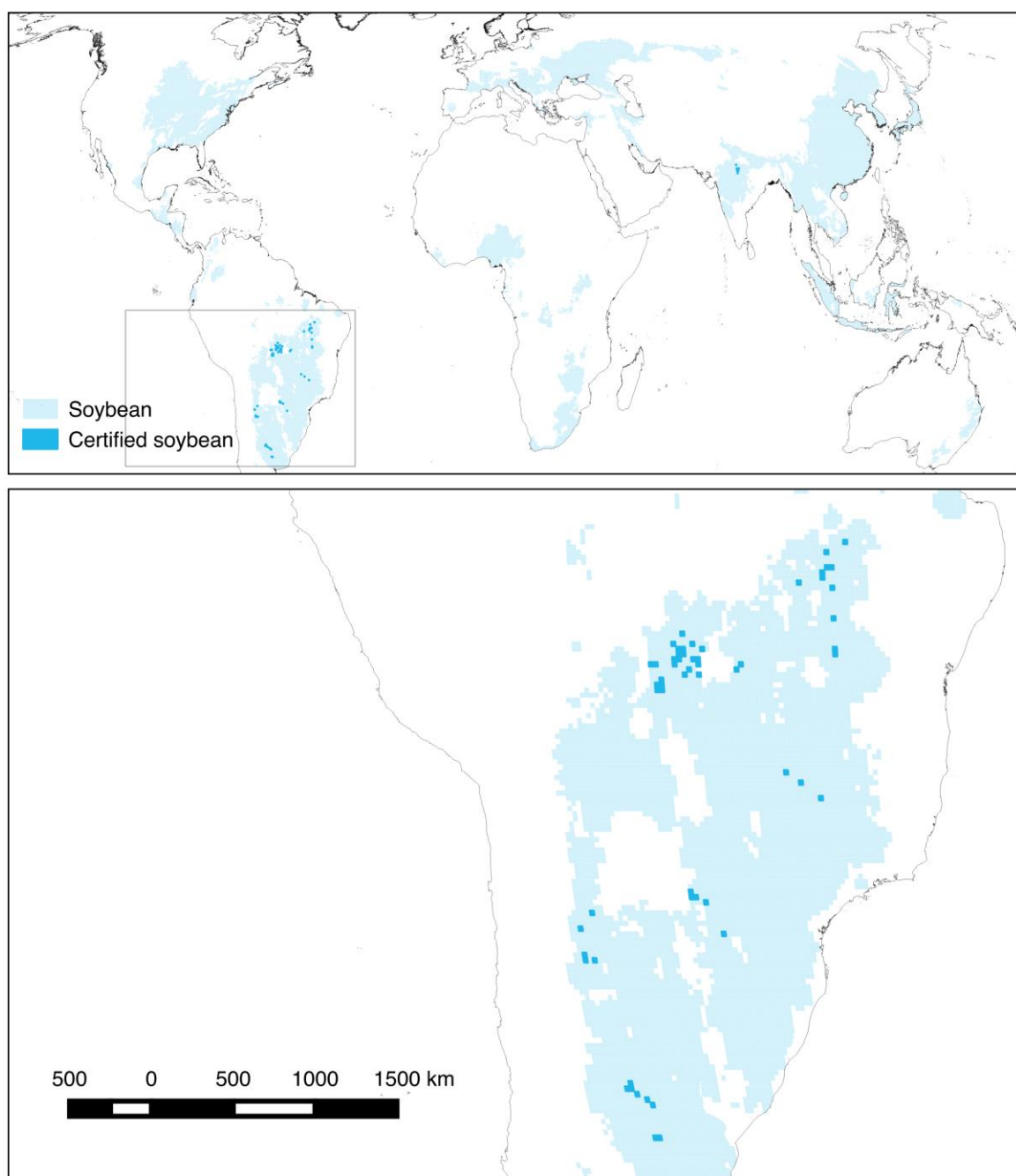
Fig. S16. Global distribution of soybean, and of certified soybean. Lower inset shows area with most certified soybean (South America) in more detail.
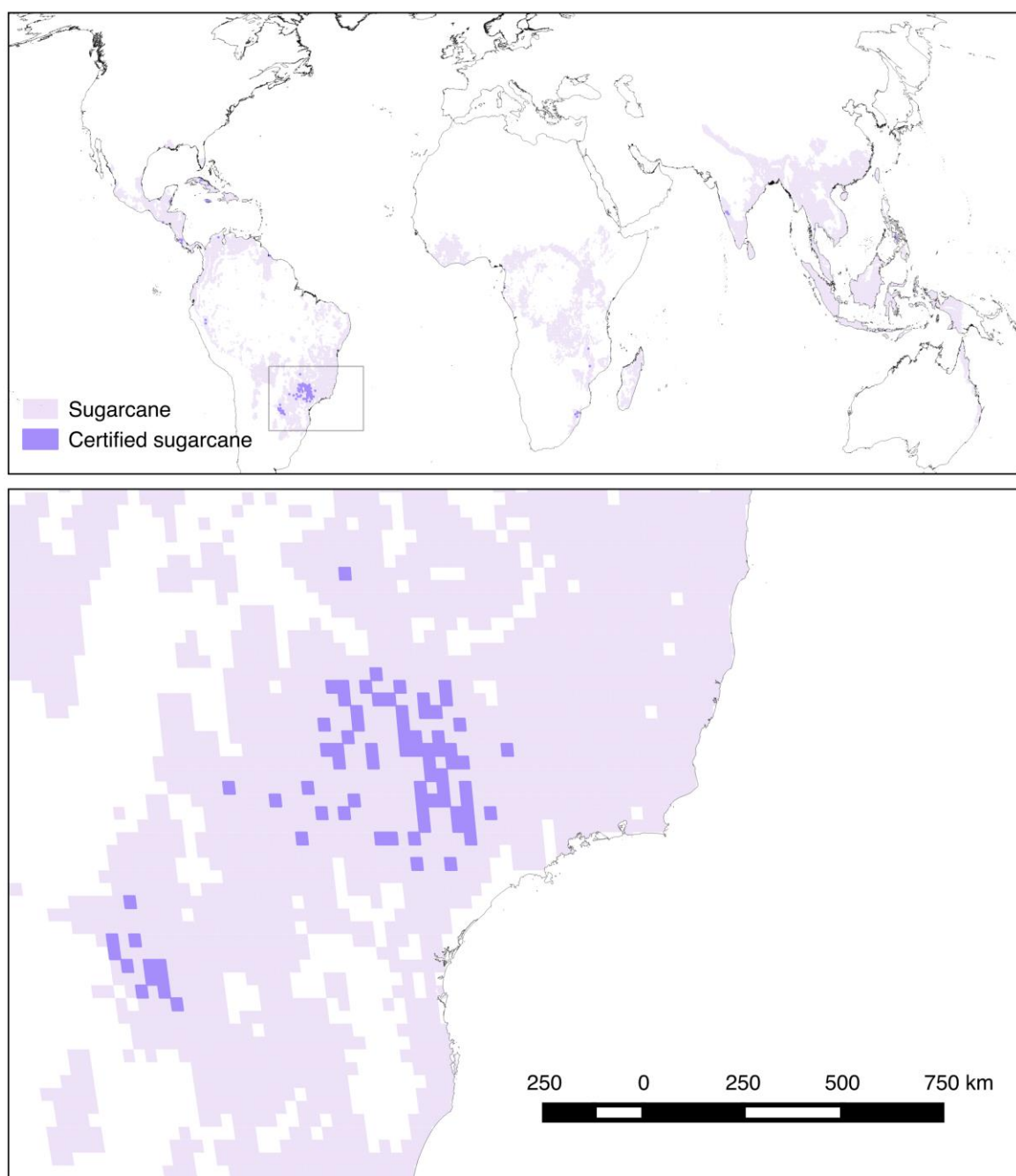
Fig. S17. Global distribution of sugarcane, and of certified sugarcane. Lower inset shows area with most certified sugarcane (Brazil and Paraguay) in more detail.
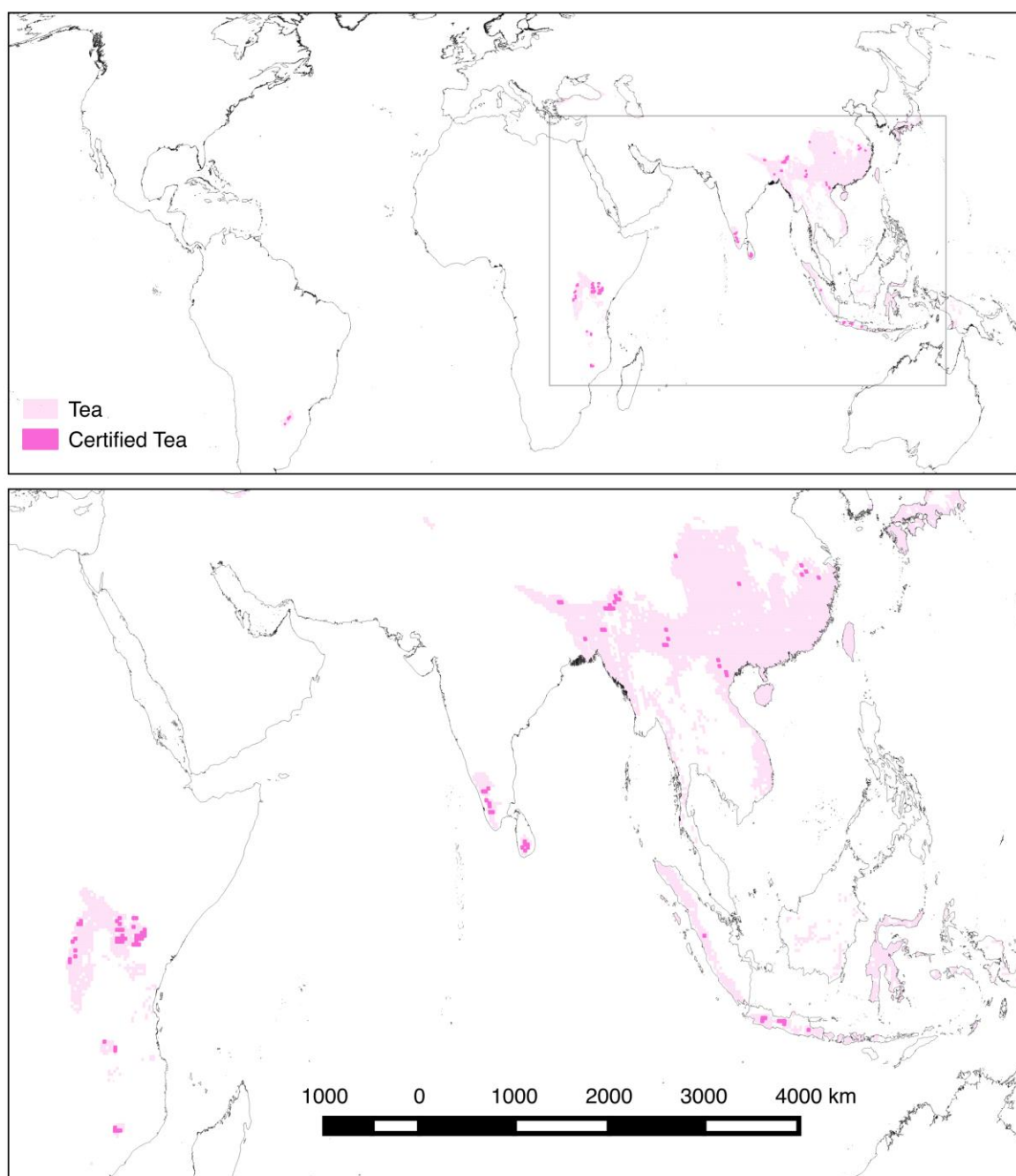
Fig. S18. Global distribution of tea, and of certified tea. Lower inset shows area with most certified

tea (East Africa and Asia) in more detail.
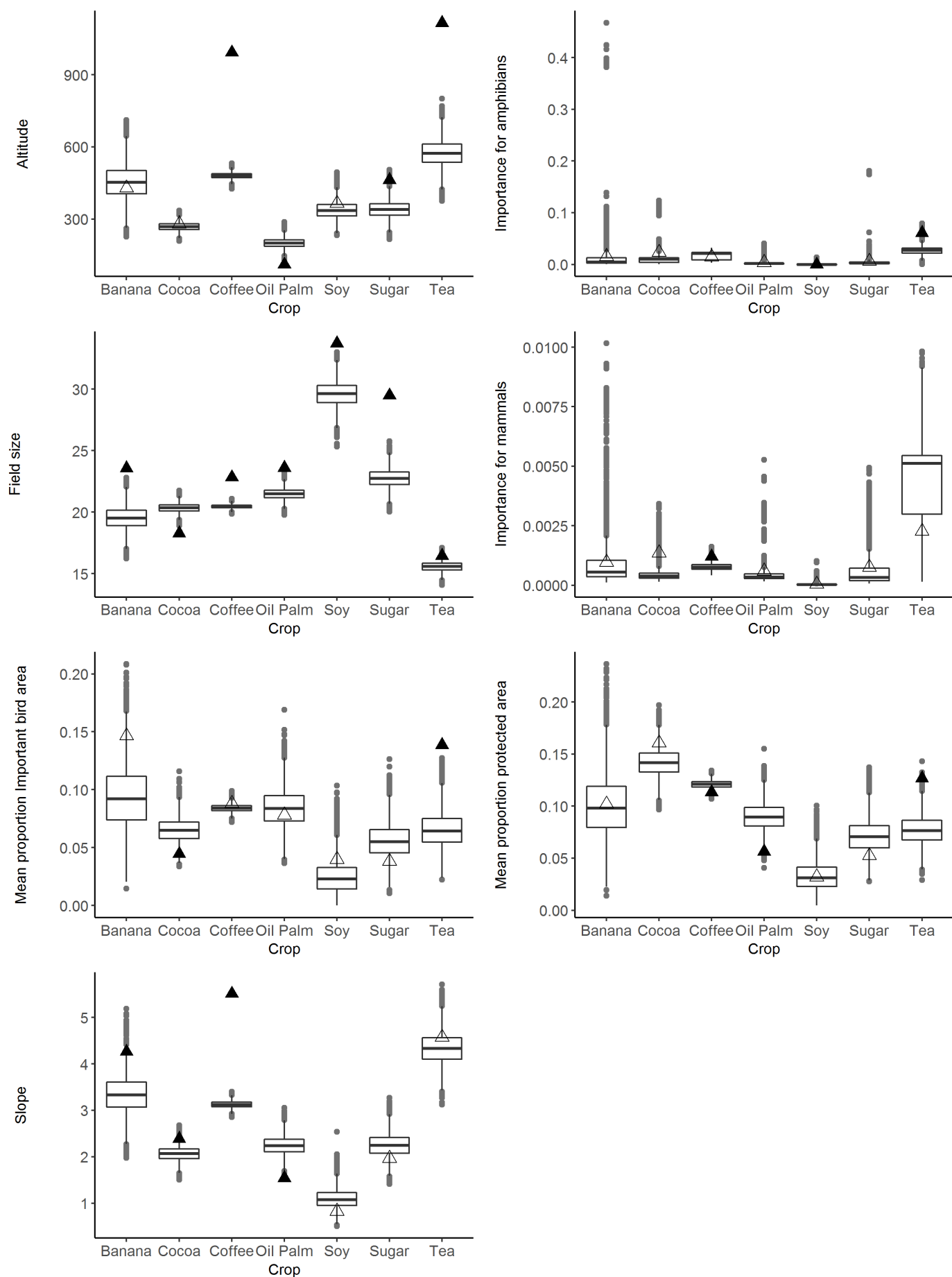
Fig S19. The distribution of values for a selection of variables across their global crop-growing range shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each boxplot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
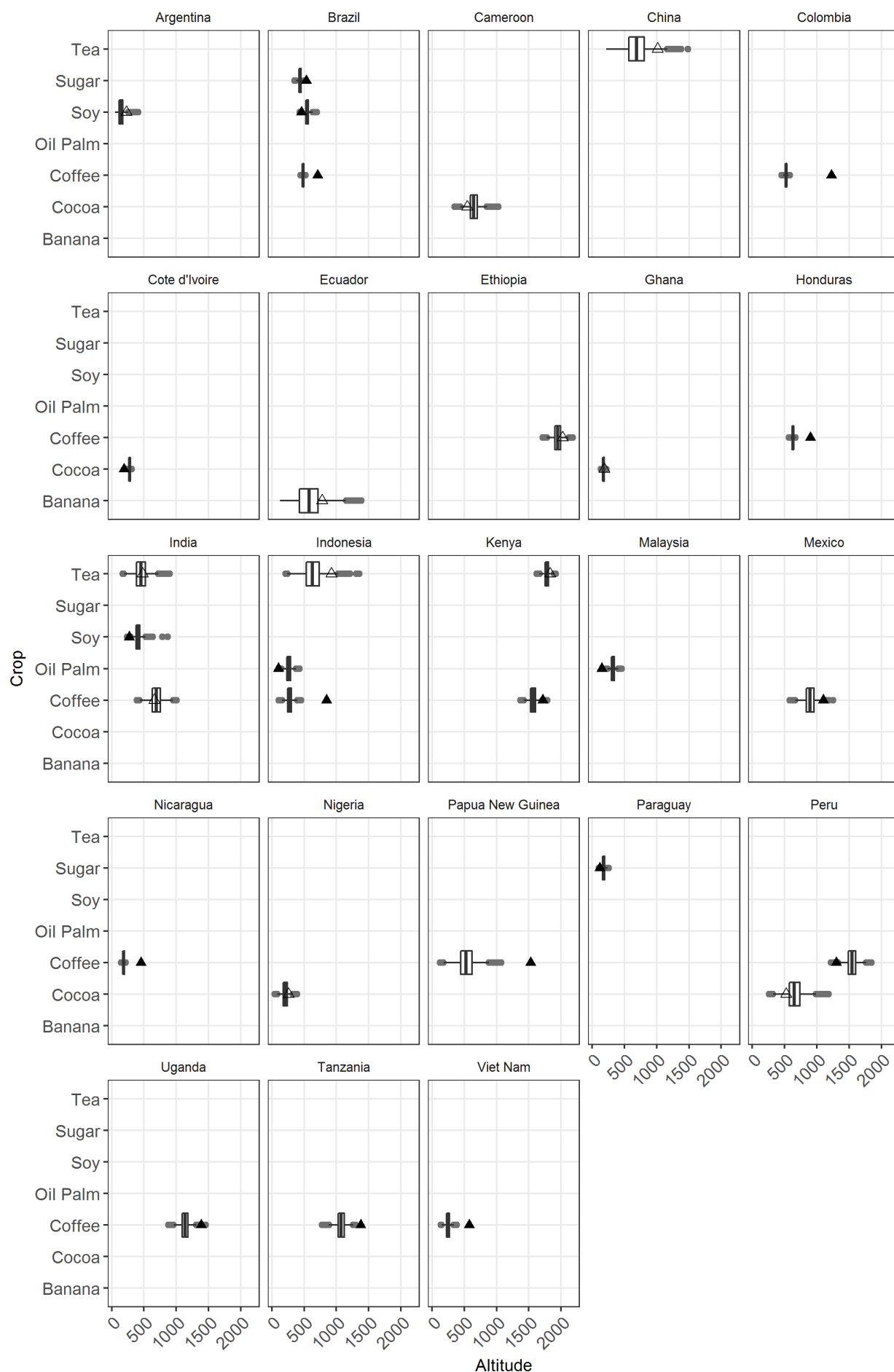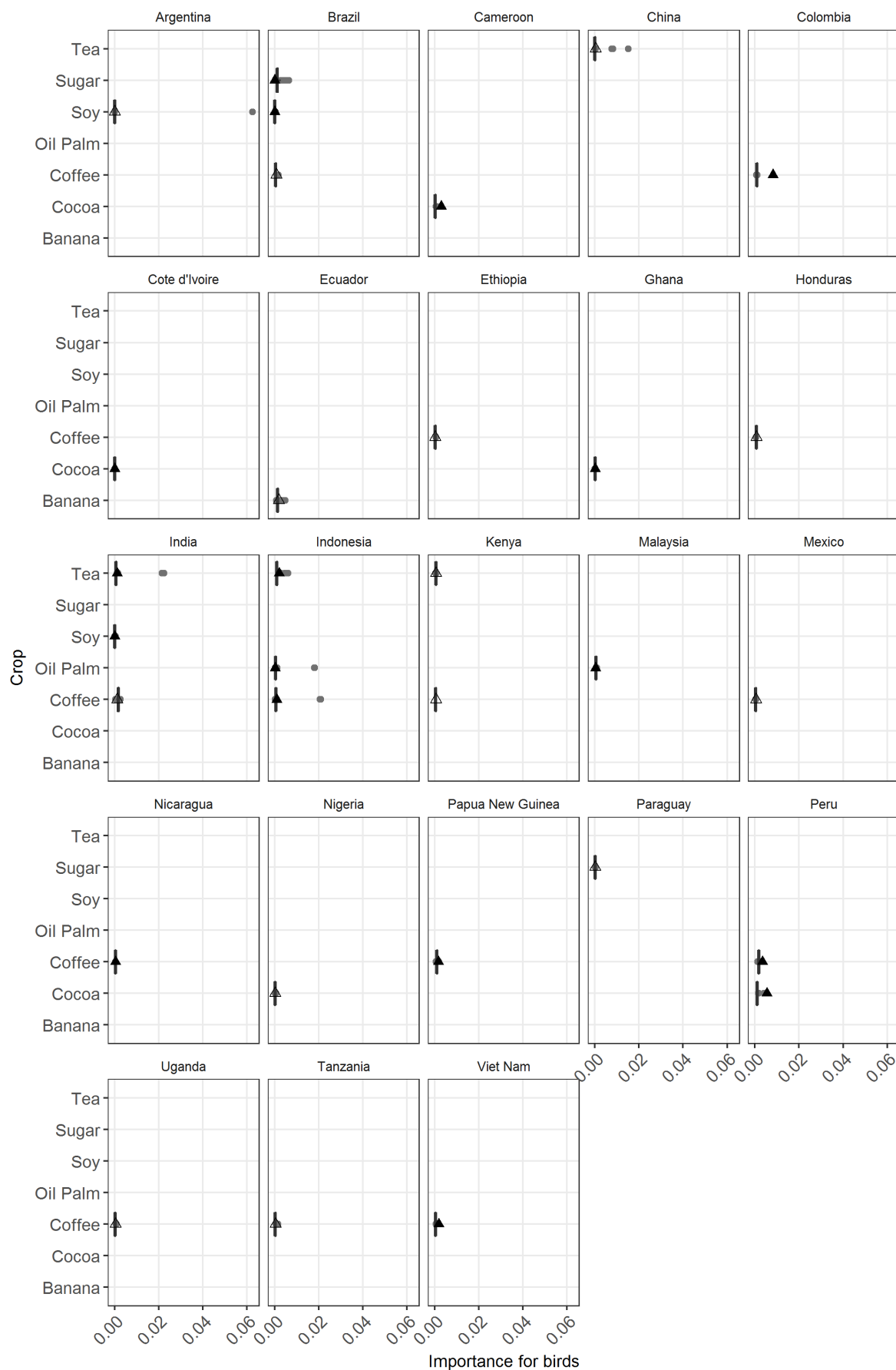
Fig S20. The distribution of values for altitude (metres) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
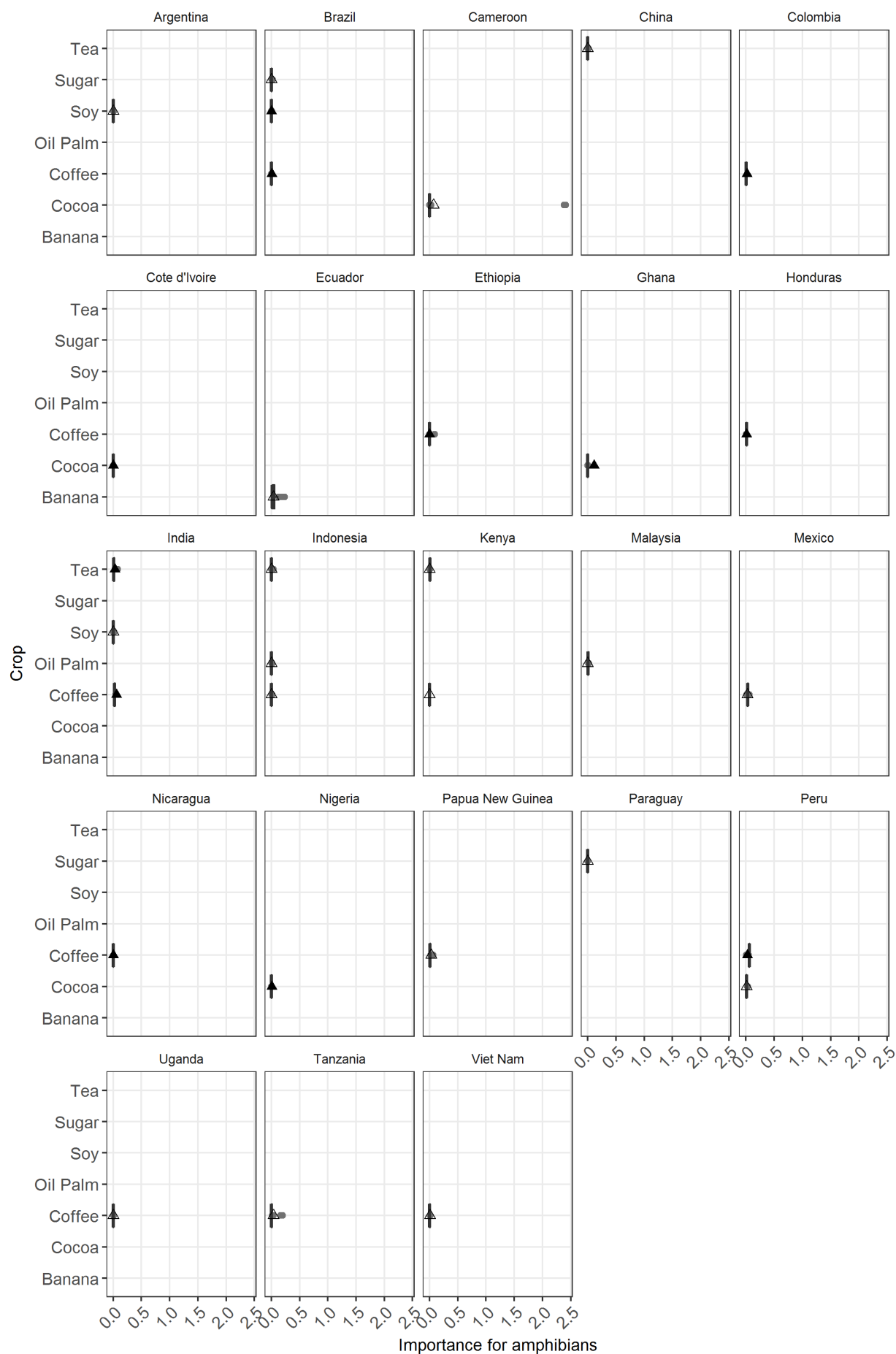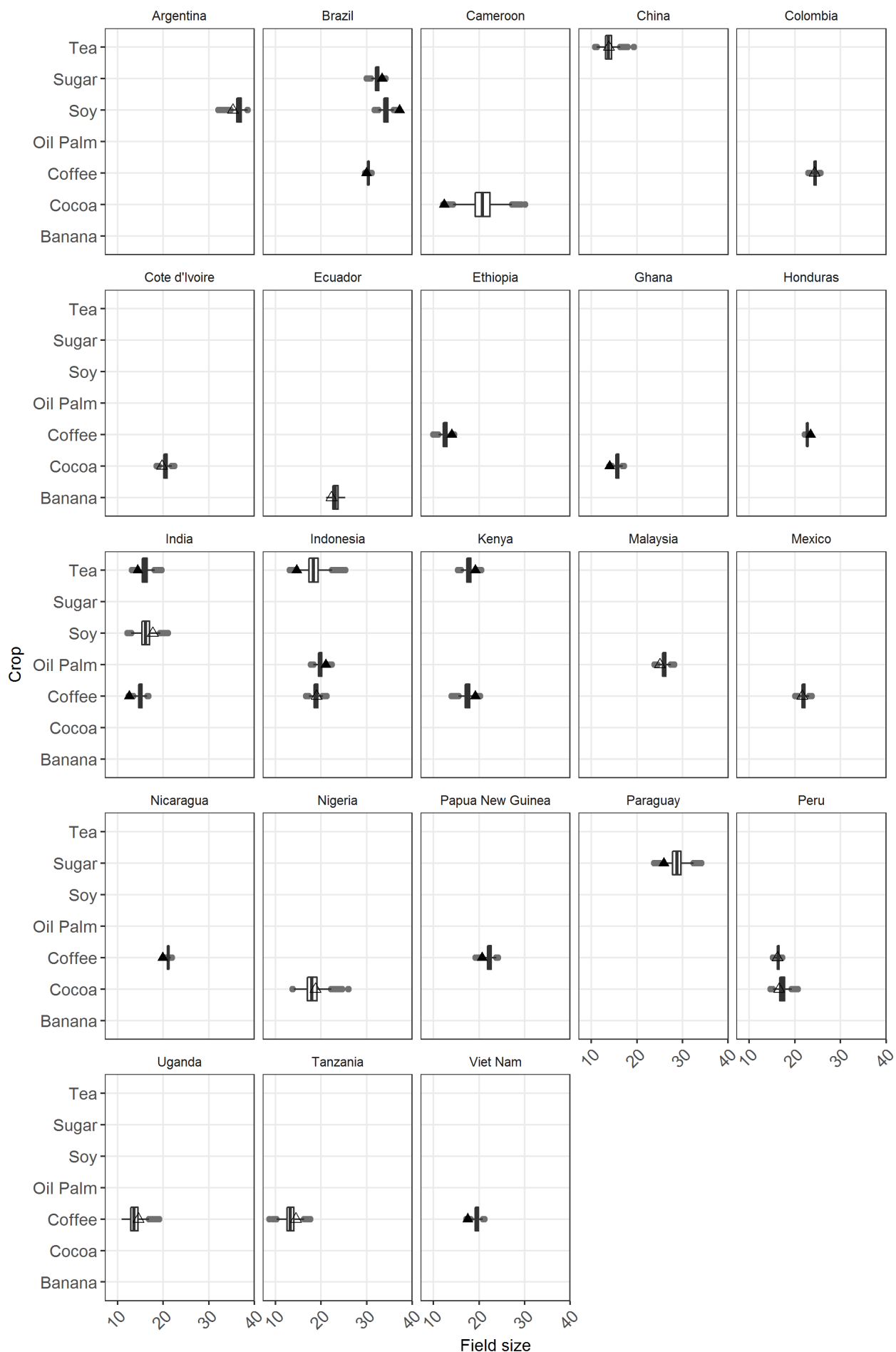
Fig S21. The distribution of values for importance for amphibians (see main text for explanation of units) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
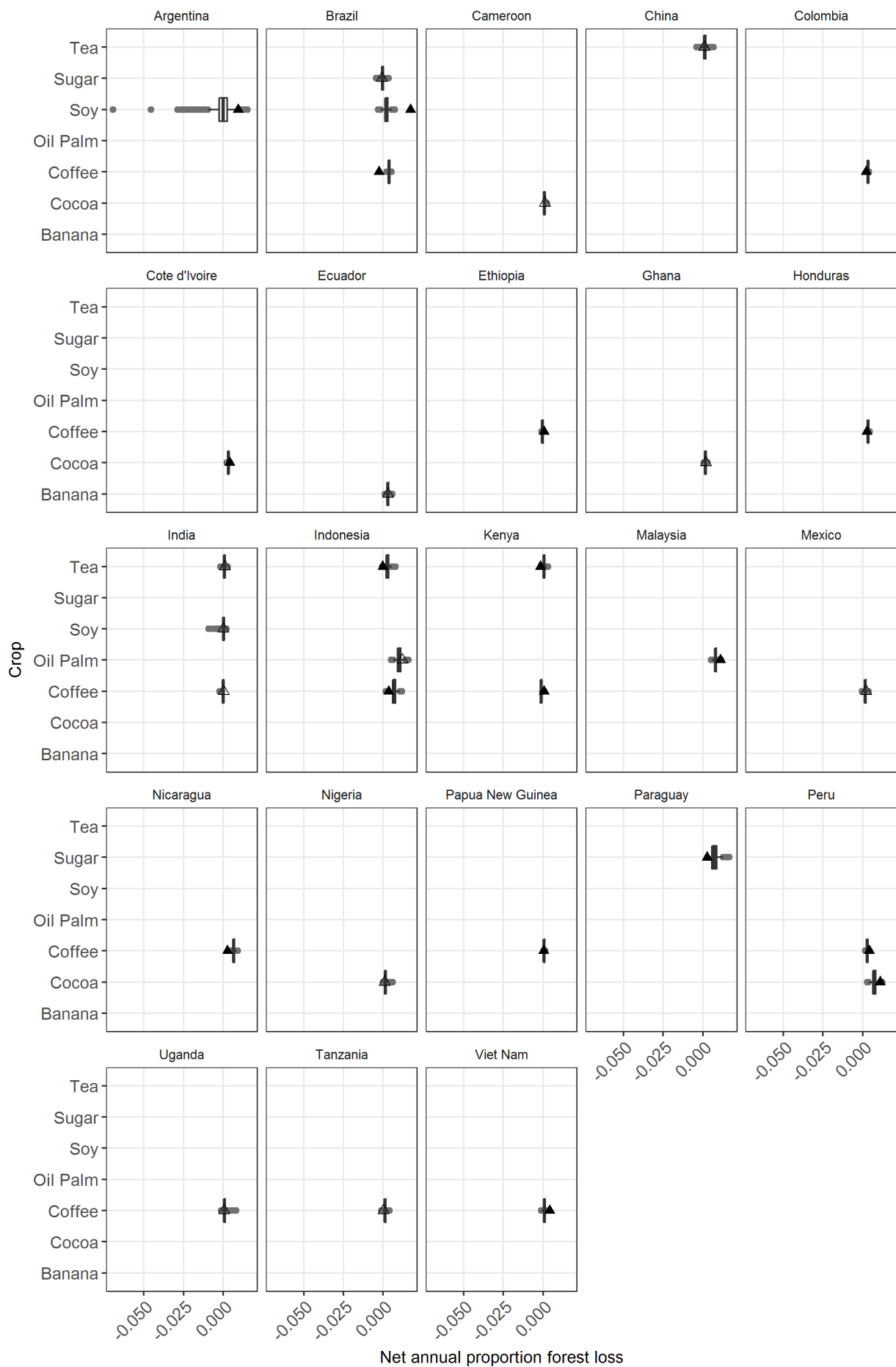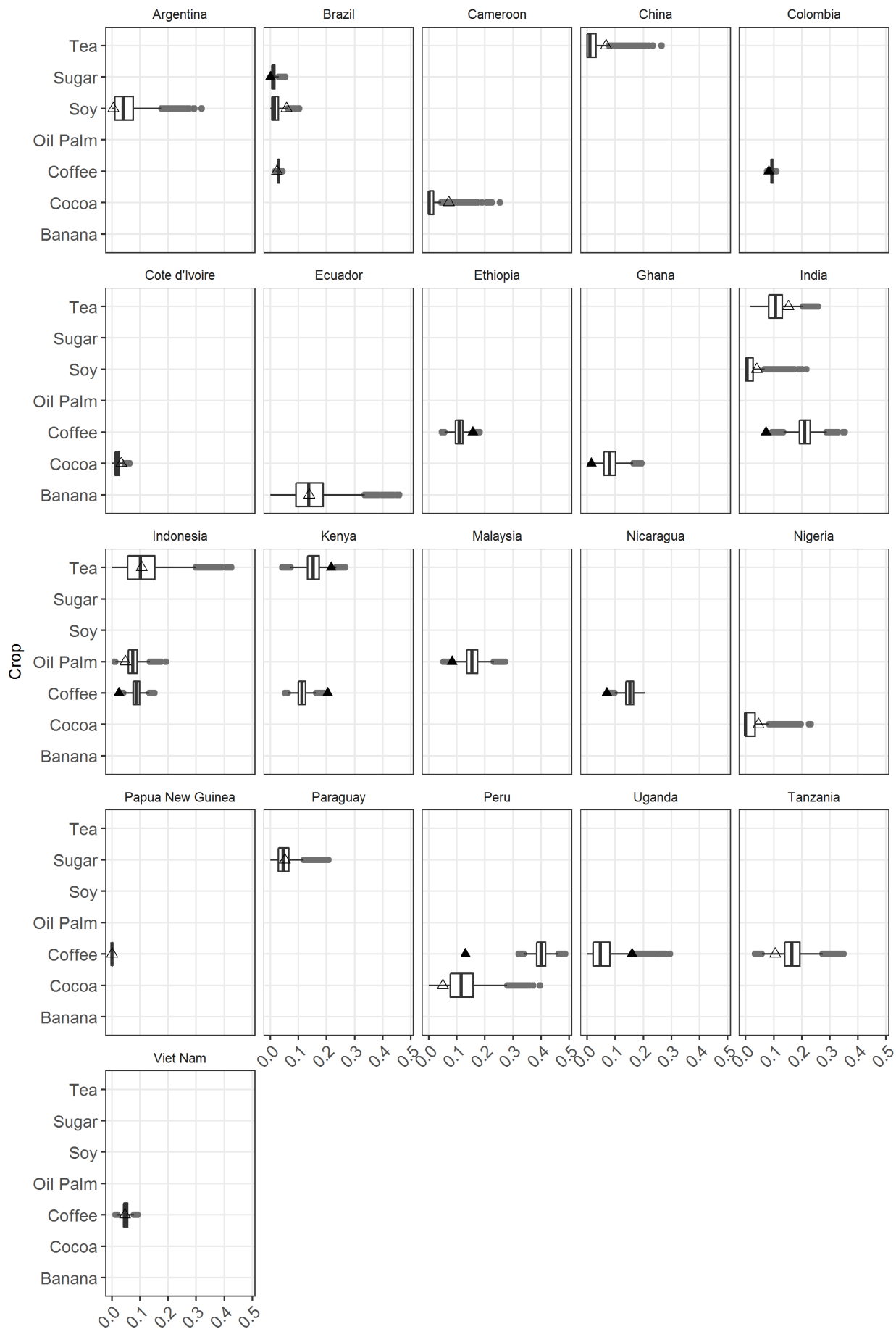
Fig S22. The distribution of values for importance for birds (see main text for explanation of units) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.

Fig S23. The distribution of values for field size (arbitrary units) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.

Fig S24. The distribution of values for mean annual proportion net tree cover loss (negative values refer to tree cover gain) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
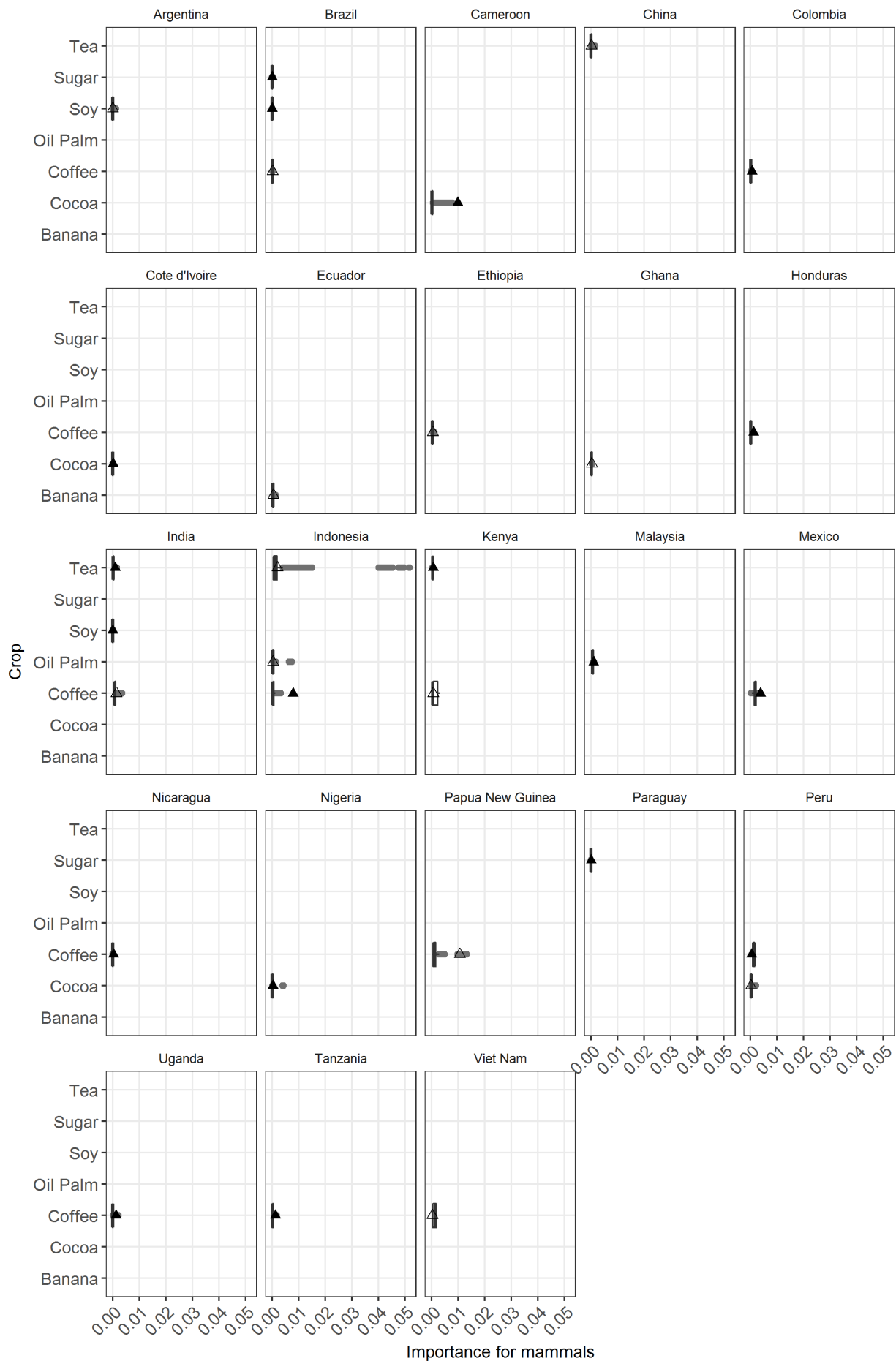
Fig S25. The distribution of values for mean % Important Bird and Biodiversity Areas for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
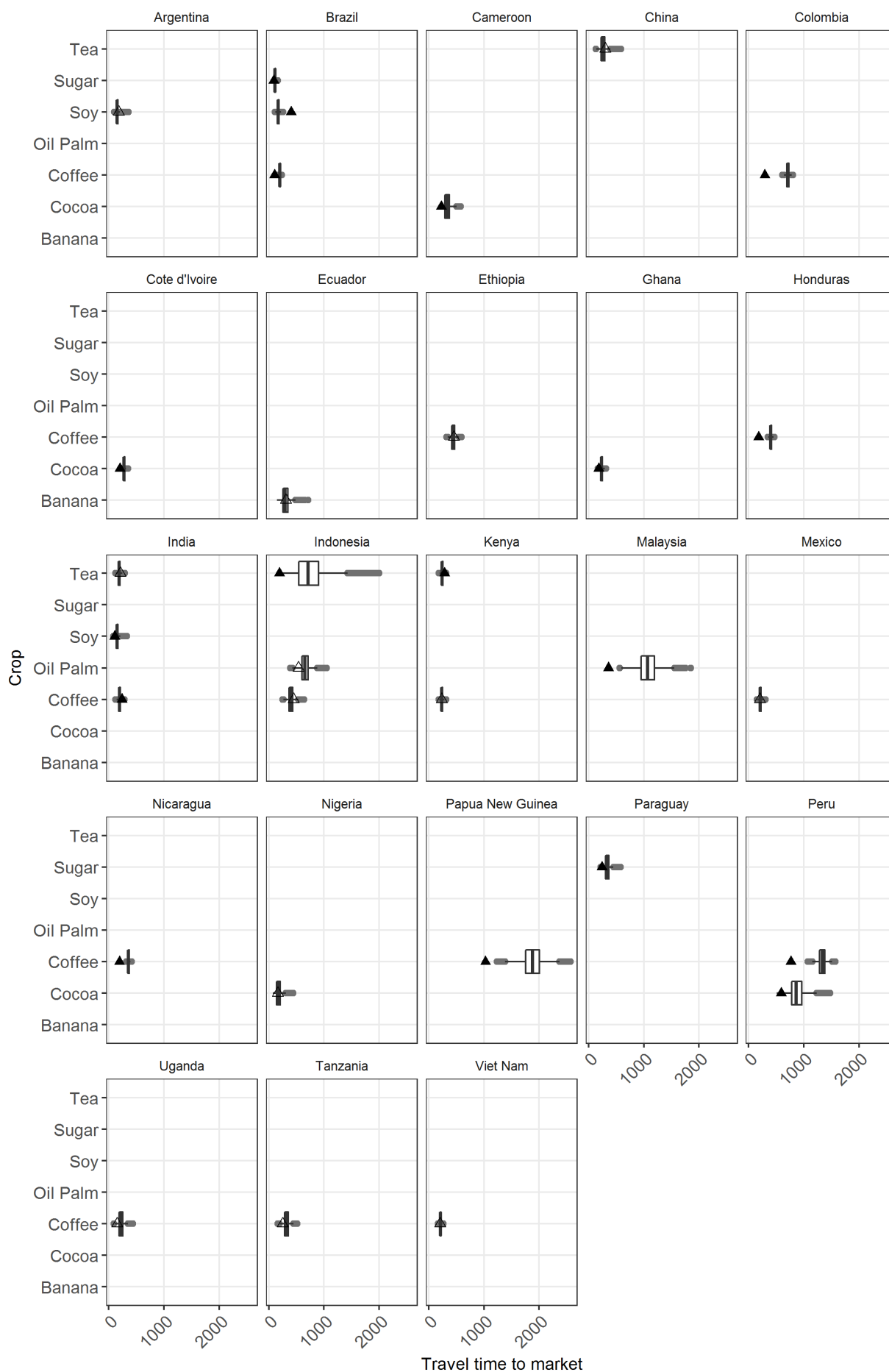
Fig S26. The distribution of values for importance for mammals (see main text for explanation of units) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
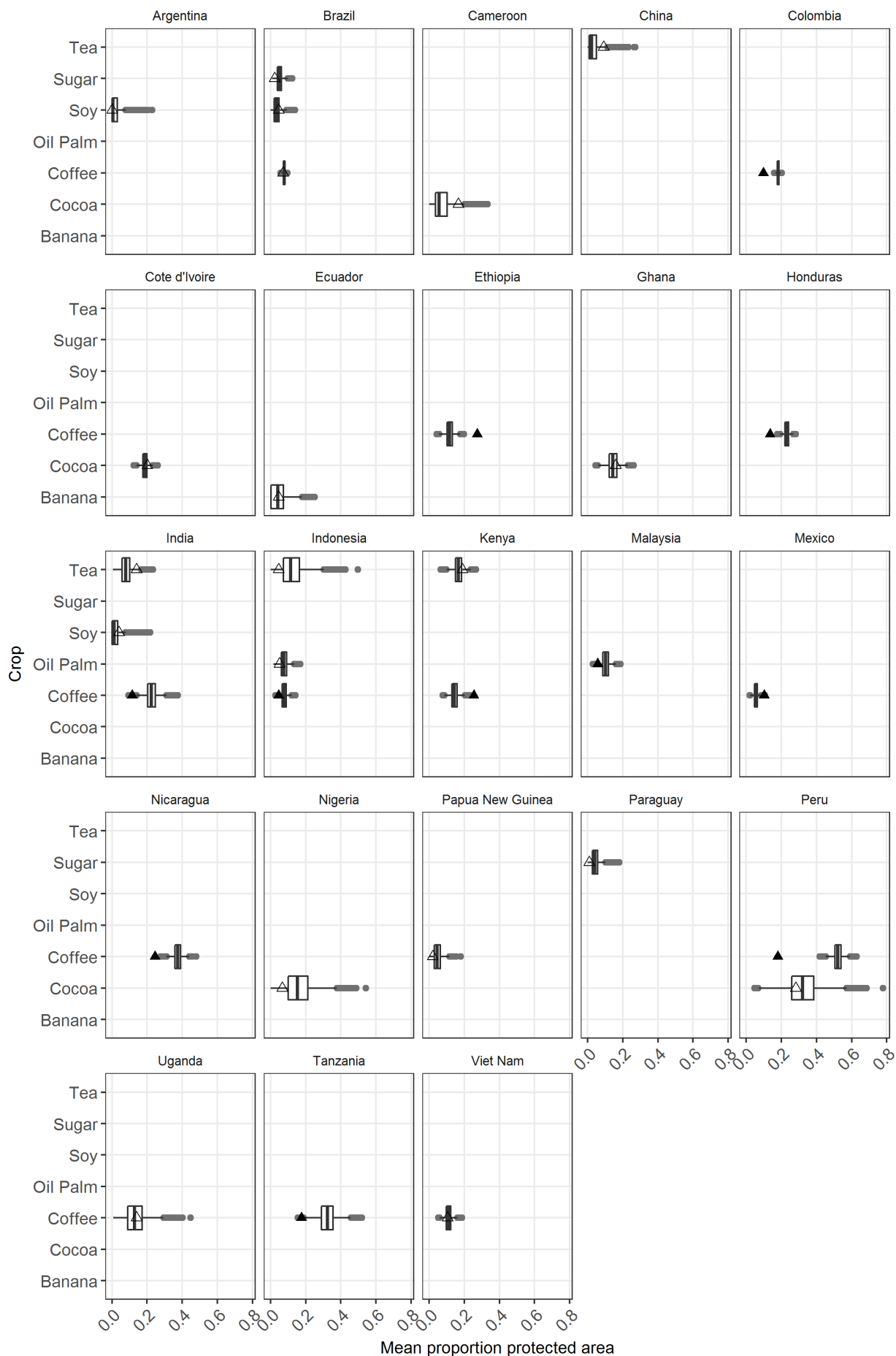
Fig S27. The distribution of values for travel time (minutes) to the nearest market for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.

Fig S28. The distribution of values for mean % Protected Area for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
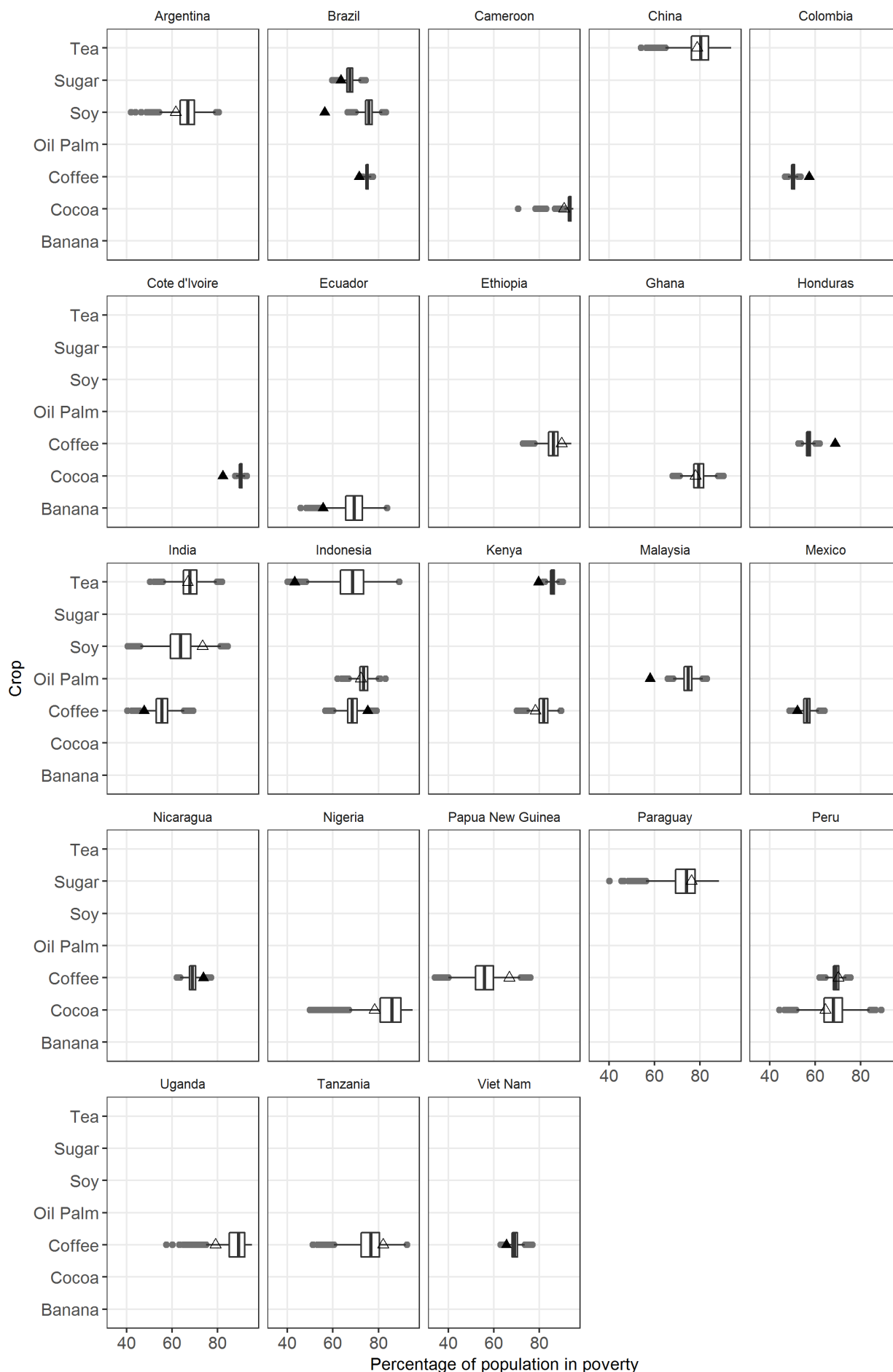
Fig S29. The distribution of values for the mean percentage of the population in poverty across each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.
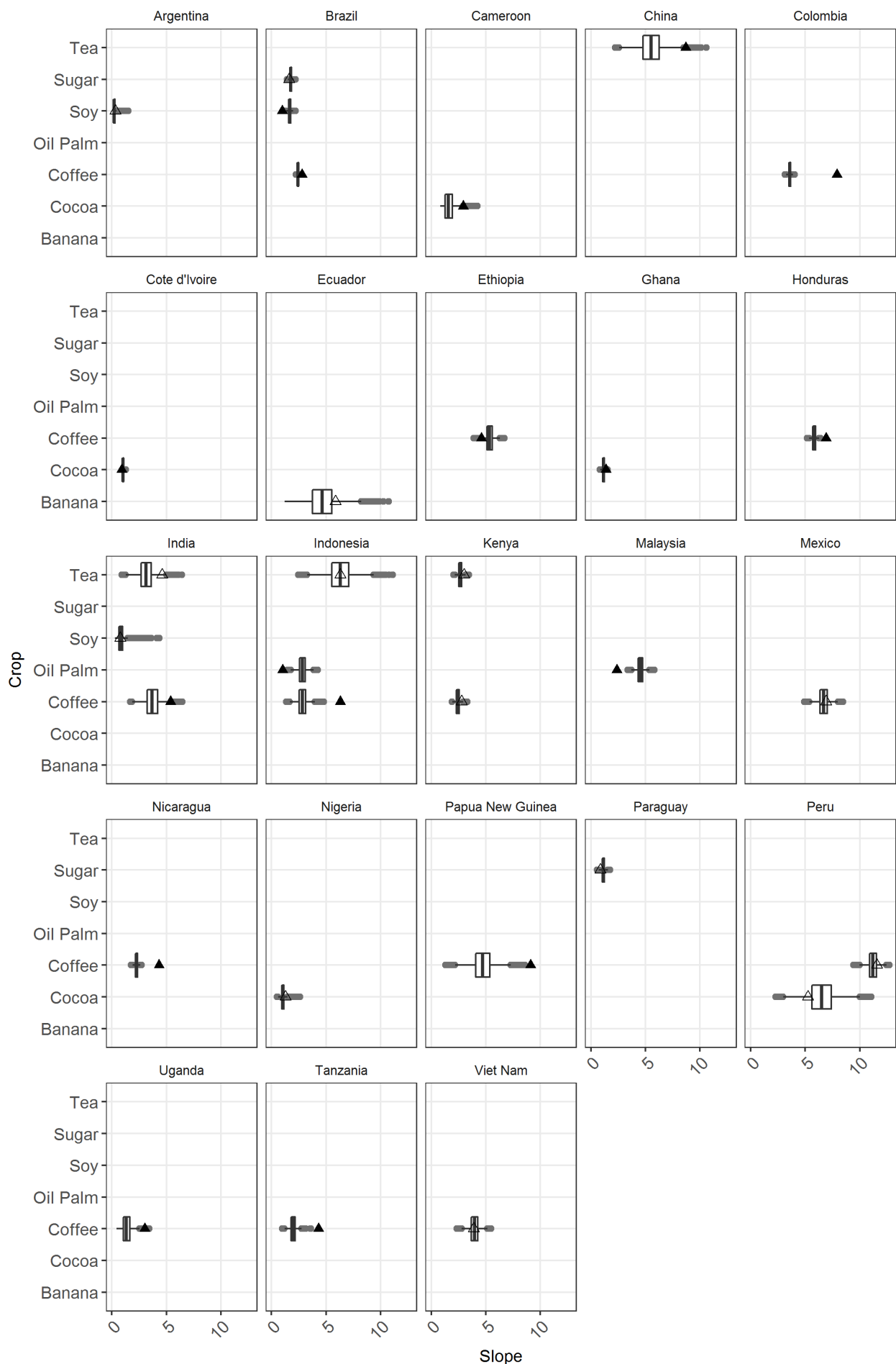
Fig S30. The distribution of values for slope (degrees) for each crop-growing country shown using box plots. The value for certified grid cells is signified by an open triangle where the value was not significantly different from the global distribution, and by a solid triangle when they were significantly different. Each box plot represents 10,000 random sub-samples, equal in area to our certified sample, drawn without replacement from non-certified grid cells.

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