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# Perceptions of climate and climate change by Amazonian communities

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**Abstract** The Amazon region has been undergoing profound transformations since the late '70s through forest degradation, land use changes and effects of global climate change. The perception of such changes by local communities is important for risk analysis and for subsequent societal decision making. In this study, we compare and contrast observations and perceptions of climate change by selected Amazonian communities particularly vulnerable to alterations in precipitation regimes. Two main points were analysed: (i) the notion of changes in the annual climate cycle and (ii) the notion of changes in rainfall patterns. About 72% of the sampled population reports perceptions of climate changes, and there is a robust signal of increased perception with age. Other possible predictive parameters such as gender, fishing frequency and changes in/planning of economic activities do not appear overall as contributing to perceptions. The communities' perceptions of the changes in 2013-2014 were then compared to earlier results (2007-2008), providing an unprecedented cohort study of the same sites. Results show that climate change perceptions and measured rainfall variations differ across the basin. It was only in the southern part of the Amazon that both measured and perceived changes in rainfall patterns were consistent with decreased precipitation. However, the perception of a changing climate became more widespread and frequently mentioned, signalling an increase in awareness of climate risk.

**Keywords** Climate change, Perceptions, Amazon, Remote Sensing

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## 34 **1 Introduction**

### 35 *1.1 Climate change debate and perceptions*

36 In recent decades, climate change has taken a central place in scientific, political, economic and  
37 public arenas. Several studies have shown evidence of recent changes in weather and climate  
38 patterns, and the scientific community overwhelmingly agrees that the Earth's atmosphere has  
39 been warming up due to the continual emission of greenhouse gases (e.g., IPCC 2014, 2018 and  
40 references therein). These changes in Earth's climate have environmental, socio-political and  
41 economic consequences as weather dependent resources and activities can be compromised,  
42 leading to potential conflicts. Denial of climate change, particularly by governmental and policy-  
43 making actors, is a serious issue as it hinders efforts for mitigation and adaptation strategies,  
44 which the latest IPCC report (2018) reiterated was urgent. Some in the private sector already  
45 weigh in on the impact of climate change - ranging from increase in operational costs to  
46 disruption in production - even though there are limitations to adaptation strategies (Goldstein  
47 et al. 2019).

48 The study of perceptions is important as a support for risk analysis and for preparing  
49 public response to hazards. It can also help in communicating risk information among the local  
50 population, the technical experts and the policy makers (Noble et al. 2014, Sterman 2008,  
51 Farjam et al. 2018). Rudiak-Gould (2014) showed that climate science communication has a  
52 significant impact on climate perceptions: climate science awareness was a better predictor of  
53 environmental change perceptions than exposure to the environment. If we start with the  
54 hypothesis that mitigation of (and/or adaptation to) climate change is linked to first-hand  
55 experience of its potential consequences (for example, higher frequency and intensity of  
56 droughts, floods, heat waves or cold spells, etc.), then it follows that individuals who have had  
57 these experiences may be more inclined to adopt sustainable behaviours and/or adaptation  
58 practices (Spence et al. 2011, and references therein). This hypothesis has been tested in the US  
59 and the UK with mixed results. Spence et al. (2011) and Rudiak-Gould (2014) found that people  
60 affected by floods became more responsive and sensitive to energy and climate change issues,

61 while Coles and Scott (2009) found that, due to economic constraints (cost of adaptation),  
62 traditional knowledge is favoured instead of seasonal climate predictions in defining  
63 agricultural and ranching practices. Understanding the underlying drivers that encourage local  
64 people to adapt to climate change helps with forging programs and strategies that can have a  
65 better chance for a positive outcome (Slovic et al. 1982; Leiserowitz 2006; Weber 2006, 2010;  
66 Howe et al. 2013; Neetheling et al. 2016; Spence et al. 2011, Noble et al. 2014, Bakaki and  
67 Bernauer 2017).

68

### 69 *1.2 Climate change observations in the Amazon Region*

70

71 The Amazonian ecosystem is a major component of the Earth system, playing a key role in the  
72 water and carbon global cycle. There have been numerous studies in the past three decades on  
73 the complex interaction between global-scale climate change and deforestation (which could  
74 locally exacerbate climate change effects) and the impacts of climate change on biodiversity,  
75 ecosystem services, and most recently health (e.g., Shukla et al. 1990; Gash et al. 1996; Laurance  
76 et al. 2001; Betts et al. 2004; Malhi et al., 2008; Nobre et al. 2016; Ochoa-Quintero et al. 2015;  
77 Barlow et al. 2016, Brondizio et al. 2016, Parry et al. 2017, Zemp et al. 2017, Rao et al. 2019).

78 Several climate studies based on observations and numerical model simulations of the  
79 climate in the Amazon have pointed to an increase in temperature, as well as a decrease in the  
80 duration of the rainy season and a strengthening of the water cycle and runoff (e.g., Oyama and  
81 Nobre 1990, Fu et al. 2013, Debortoli et al. 2015, Goor et al. 2013, Guimberteau et al. 2017,  
82 Arvor et al. 2017b, Nobre et al. 2016). The combined effect of large-scale climate change and  
83 local deforestation is more difficult to assess. For example, the impact of the Amazon  
84 fragmentation on climate is not well understood, and land cover subsequent to deforestation is  
85 an important factor on the degree of projected climate change (Sampaio et al., 2007, Correia et  
86 al. 2008, Malhi et al. 2008). A range of climate model studies showed a trend toward forests  
87 being replaced by lower vegetation (savanna or seasonal forests) in the southern part of the

88 Amazon that was caused by a combination of the effects of increased temperature and a longer  
89 dry season, this forecasted in most models by 2100 (Cook et al., 2013). In addition, years with  
90 more intense floods (such as those of 2009 and 2014) could increase forest resilience by  
91 providing a surplus of residual soil moisture that would be available for the following year.  
92 Thus, there are various forcings and uncertainties in the climate projections. These  
93 uncertainties propagate through temporal and spatial scales, but there is evidence that, mainly  
94 in its southern and eastern parts, the Amazon basin ecosystem is transitioning to a disturbed  
95 regime with changes in the energy and water cycles (Davidson et al. 2012). At a regional scale  
96 such as the Amazon, it is necessary to consider several nested spatial scales to address the  
97 impact of climate change on ecosystems. Deforestation, agricultural practices, road construction  
98 and other activities contribute to the degradation of the forest ecosystem and resources and  
99 influence local and regional climate, the economy and public health (Davidson et al., 2012;  
100 Brondízio et al. 2016, Nobre et al. 2016).

101

### 102 *1.3 Reconciling climate change observations and perceptions in the Amazon region*

103 In the Amazonian context, many traditional communities depend on rivers for their  
104 livelihood at several levels and are therefore impacted by more pronounced variations in  
105 precipitation and water levels. For example, fishing may turn into an economically risky activity  
106 should there be repeated droughts. For remote or isolated communities, floods and droughts  
107 can impact access and export of their production, leading to potential degradation of living  
108 conditions (Parry et al. 2017). Agriculture-based activities are impacted by fluctuations in water  
109 availability and solar irradiance (Pires et al. 2016). However, we do not yet have enough studies  
110 on the perceptions of climate change by these Amazonian communities.

111 A study on how traditional knowledge and meteorological data influence family-scale  
112 farming has demonstrated that local farmers in the semi-arid Northeast of Brazil do not change  
113 their practices, mostly because of the lack of both technical and cultural alternative solutions

114 (Nasuti et al. 2013). In the latter case, all actions - or reactions - to perceived changes were  
115 aimed at short-term solutions, not long-term plans for adaptation.

116 An initial investigation on perceptions of climate change by Amazonian communities  
117 was performed by the DURAMAZ project (Dubreuil et al. 2017; Le Tourneau and Droulers  
118 2010). These Amazonian communities were the subject of a broad study on sustainable  
119 development and were selected to represent the diversity of the rural, heterogeneous  
120 population in the Amazon region. In 2007-2008, Dubreuil et al. (2017) performed a cross-  
121 analysis of local precipitation trends with results from specially elaborated questionnaires on  
122 climate change perceptions from these selected sites. They showed that perceptions of climate  
123 change varied, as did the agreement with physical, measured data. Only communities within the  
124 arc of deforestation (the south and southeastern Amazon) presented consistency between  
125 downward trend of rainfall (Debortoli et al. 2017; Dubreuil et al. 2012; Nobre et al. 2016) and  
126 perception of rainfall change.

127 During the second phase of the DURAMAZ project (DURAMAZ-2; 2011-2015), the study  
128 of the relationship between climate change and its perception by affected communities was  
129 given more weight. The current study unfolded in two stages, first by performing univariate and  
130 bi-variate statistical analysis of independent and observed variables, then by associating  
131 measured and perceived precipitation trends data. These trends were then crossed against  
132 responses to questions on perception of climate dynamics in order to evaluate the  
133 dis/similarities between observation and perception rainfall trends detected in the Amazon  
134 basin. The analysis of perceptions was further reviewed in the context of agricultural practices  
135 and links to climate change perceptions. Finally, the study targeted the same communities with  
136 a span of approximately 6 years apart, making it the first cohort study to follow perceptions of  
137 climate change by Amazonian communities.

138

## 139 **2 Data and Methods**

140

141 2.1 Study sites and questionnaires

142

143 The perception of climate change by local inhabitants was one of the main focuses of the  
144 DURAMAZ-2 project. Extensive fieldwork campaigns were conducted in 13 selected sample sites  
145 shown (in red) in Figure 1 and listed in Table 1. Among these 13, five are family-scale  
146 agricultural sites (Anapu, Parauapebas, Carlinda, Ouro Preto do Oeste, Juína), one to  
147 “agribusiness” (Sorriso), six are traditional communities located within protected areas  
148 (Iratapuru, Mamiraua, Tupé, Ciriaco, PAE Chico Mendes, Oyapock), and one is an indigenous  
149 community within a protected area (Moikarako). A description of the sites and their main  
150 characteristics are shown in Table 1 (see also Table 2 of Le Tourneau et al., 2013).

151 Figure 2 shows a synthetic chart depicting the methodology process used to gather data  
152 on both independent and outcome (perception) variables. The methodology employed sought  
153 an optimal social-demographic sampling of the population (Dubreuil et al. 2017; Le Tourneau et  
154 al. 2013) and used a scale refinement at each stage. First, general information on institutional  
155 and geographical aspects were collected at site scale. Socio-economic data were then collected  
156 at the household level by means of a specific questionnaire, and further completed by another  
157 questionnaire at the individual level. The sampling rules were to interview all households for  
158 sites with fewer than 75 houses or conduct a representative sampling of the population in sites  
159 that had more than 75 houses. For each house included in the sample, interviews based on the  
160 individual questionnaire were conducted with the head of household and his/her spouse, as  
161 well as with any children aged 15 or older. Thus, individual questionnaires could explore  
162 differences in behaviour and in perceptions across several age groups. In total, 747 households  
163 were visited, 1271 individuals were interviewed, and information was recorded on 2258 people.

164 The analysis of perceptions of climate in the current study was inspired by the work  
165 performed by the Brazilian Network on Global Climate Change Research (“Rede CLIMA”; Arraut  
166 et al. 2012, Lindoso et al. 2014). The communities’ economy, such as crops, livestock and  
167 extractivism, strongly depends on natural resources. The close relationship between these and

168 the climate - in particular precipitation - makes these communities vulnerable to projected  
169 and/or ongoing climate changes (Arraut et al. 2012, Nobre et al. 2016). The central and  
170 southern parts of the Amazon which are under the influence of the South American Monsoon  
171 System (Marengo et al. 2012; Vera et al. 2006) present well-defined rainy and dry seasons,  
172 roughly an austral summer and winter respectively. In the northern part, rain is present most of  
173 the year, with seasonality represented by periods of more or less precipitation. Due to the  
174 importance of rainfall variations (especially for the communities that depend largely on water  
175 availability), the analysis of perceptions was organized around two main criteria: (i) perception  
176 of changes during the rainy/dry seasons (annual climate cycle), and (ii) perception of changes in  
177 rainfall patterns.

178 In case (i), the question "What changes did you perceive in the climate?" allowed for 6  
179 answers: "No changes", "Both dry and rainy seasons changed", "Only the dry season changed",  
180 "Only the wet season changed", "Don't know/Didn't answer", "Other". In case (ii), the question  
181 "Since event x, what changes did you notice?" allowed for 7 options: "Stronger rain", "Weaker  
182 rain", "Displacement of the rainy season", "Unpredictability", "More frequent rain", "Less  
183 frequent rain", "No changes". Open-type answers (such as "Other") and spontaneous comments  
184 were carefully annotated and later code-converted in order to perform an objective analysis. We  
185 must point out that the questionnaires were focused on perceptions of precipitation changes,  
186 and yet temperature, wind and humidity changes were also brought up in the responses  
187 through "open answers", indicating that perceptions of changes of climate as a whole were  
188 present. A question on the attribution of climate change was also introduced in the form of open  
189 answers, allowing for spontaneous, unbiased remarks.

190 As a first step, univariate analysis was performed to obtain a general overview of the  
191 sample population and perceptions. A bivariate analysis was then performed to cross-evaluate  
192 the relationship between independent variables and perceptions. Notice that the liaison  
193 between sites, households and individuals was made through household indexing per site. For



194 each household only one individual answer was considered, that of the household head who was  
195 usually the eldest member of the family.

196 Answers to the questions were further scrutinized by putting them into perspective with  
197 respect to spatial distribution of the study sites and economic activity, potentially explaining the  
198 perceived changes by distinct Amazonian communities. Finally, since climate change - observed  
199 or perceived - influences strategies of planting, the planning of agricultural crops was also taken  
200 into account for the agricultural sites.

201

## 202 *2.2 Rainfall data: sources and linear trends*

203

204 In this study, we analysed trends in annual rainfall totals and also mean daily rainfall  
205 and the number of days with rain. The latter two parameters were used as proxies for intensity  
206 and frequency of rain. The main set of rainfall data consists in the PERSIANN-CDR  
207 ("Precipitation by Remote Sensing Information using Artificial Neural Networks - Climatic Data  
208 Record") satellite-derived precipitation estimates (Ashouri et al. 2015; Sorooshian et al. 2014).  
209 Satellite-based rainfall estimates are essential over the Amazon region as ground measurements  
210 are heterogeneous in time and space and often of dubious quality (Debortoli et al. 2015;  
211 Delahaye et al. 2015; Ronchail et al. 2002). Precipitation estimates by satellites are the only data  
212 available for localities where conventional ground-based measurements are non-existent. The  
213 PERSIANN-CDR dataset, available for the period 1983-delayed present, was recently released by  
214 the National Oceanic and Atmospheric Administration (NOAA). It provides daily precipitation  
215 estimates at a spatial resolution of 0.25° latitude by 0.25° longitude (~28 km). Data from the  
216 1983-2012 period was used except for the year 1992 which was excluded as there was no data  
217 available for February. Dubreuil et al. (2017) and Arvor et al. (2017b) showed that PERSIANN-  
218 CDR estimates can realistically capture spatial and seasonal precipitation features and  
219 differences across the basin, with spatial resolution good enough to represent the "community"  
220 scale. For this study, we estimated the long-term trends (1983-2012) of annual totals and the

221 number of days with rain using simple linear regression, and we used the methodology of  
222 Hauchecorne et al. (1991) (see also Santer et al. 2000) to measure the confidence interval of the  
223 estimated trend. The confidence interval depends on both the variance of the random  
224 component - which includes the short-term variability of the atmosphere and the measurement  
225 noise - and the correlation between two successive measurements. We provided the 2-sigma  
226 range (equivalent to 95% significance), commonly used to define the confidence interval. In the  
227 Amazon region, trends in precipitation are typically smaller than its confidence interval,  
228 indicating that natural variability of the system dominates the variability signal (e.g., Davidson  
229 et al. 2012).

230

231

### 232 **3 Results**

233 This section was structured as follows: first, univariate analysis compiling individual and  
234 household level data (Figure 2) are presented (Section 3.1). Next, in Section 3.2 we examine  
235 whether any of the independent variables appear as a predictor of perception of climate change.  
236 Finally, in Sections 3.3 to 3.5, we analyse the results at a site level for which a spatial analysis of  
237 the results and a comparison between measured and perceived rainfall data are possible. A  
238 discussion on the temporal evolution of perceptions is presented in Section 3.4.

239

#### 240 *3.1 Univariate Analysis*

241 Results of a univariate analysis are displayed in Table 2. Age, gender, fishing frequency,  
242 changes in activity and weather prediction are independent variables that were picked as  
243 predictor parameters; the latter three were chosen as proxies to the degree of exposure and/or  
244 sensitivity to the surrounding environment. For example, one would expect that those who rely  
245 on personal experience to predict the upcoming weather or make changes in agricultural  
246 planning would be more sensitive to variations in climate.

247 Table 2 shows that the sampling was fairly equitable regarding gender (53.1% men,  
248 46.7% women) and even regarding age, with slightly more population under 40 (54.4%) than  
249 above. This proportion is close to that of the total population in rural Amazonia, which is  
250 approximately 60/40 for below/above 40 year-olds (removing those below 15;  
251 <https://sidra.ibge.gov.br/home/pms/brasil>). The other independent variables chosen  
252 (frequency of fishing, changes in activity, and weather forecasting) indicate a rather  
253 heterogeneous distribution. The outcome variables reveal an overwhelming perception of  
254 climate change in general (~72%) and of rainfall changes (~65%). Other elements of climate  
255 (winds, temperature and humidity) were also brought up spontaneously (12.7%), with  
256 increased temperature being often mentioned (11.3% of total answers). This can be partially  
257 attributed to influence from media outlets that report impacts of global warming, but it also  
258 corresponds to the (rare) temperature observations in the Amazon (e.g., Victoria et al. 1998).

259 For the “Why is the weather changing” question, 30.8% of respondents felt that there  
260 exists an anthropogenic imprint through deforestation, dam building, degradation of soil and  
261 environment (pollution, silting). For other factors such as fire, cattle ranching and road  
262 construction, 14.7% of the interviewees suggested that climate is “not changing”, “God is  
263 changing it”, or “climate is evolving naturally”. These results are site-dependent, as in Sorriso  
264 where one can suspect a bias in the response from soy producers that try to deflect any  
265 potential blame, either direct or indirect, for changes potentially linked to deforestation  
266 (Debortoli et al. 2017). On the other hand, respondents in the community of Iratapuru often  
267 brought up the construction of the Belo Monte hydro-electrical power plant (to which they are  
268 strongly opposed) as the reason for climate change.

269

### 270 *3.2 Bivariate Analysis*

271 Tables 3-7 show the results of a bivariate analysis. Results were tested for significance against a  
272 binomial distribution (2-tailed test), with the null hypothesis being a random chance of getting a  
273 yes/no answer to each perception question. All tests were performed using the raw counts for

274 each class. Results were further tested against bias in the sampling size by means of non-  
275 parametric, ranking correlation. These correlations showed that the estimated percentage  
276 values were unaffected by the sampling size, except for the “weather prediction” parameter.

277 The results show that there is a significant increase of climate change reports with age  
278 ( $r_s = 0.7$ ; Table 4), congruent with the notion of “shifted time baseline”. As stated by Hansen *et*  
279 *al.* (2011), “a perceptive person old enough to remember the climate of 1951–1980 should  
280 recognize the existence of climate change”, however those exposed to a more recent climate  
281 baseline (e.g., 1981-2010) would not have the same perception “as they include the years of  
282 rapidly changing climate within the base period, making it more difficult to discern the changes  
283 that are taking place”.

284 There is a small difference in gender-based perceptions: men are less likely to report  
285 climate change than women by ~2%, but seem more inclined by ~4% to attribute perceived  
286 changes to anthropogenic forcing compared to women (differences not statistically significant).  
287 In general, the degree of exposure to the surrounding environment does not seem to influence  
288 perceptions of change, the only exception being the significant and negative (Spearman rank)  
289 correlation ( $r_s = -0.8$ ) between the frequency of fishing and reports of climate change other than  
290 rain (mostly reporting warmer climate; Table 5). One explanation could be that areas next to  
291 the river are fresher, leading to a stronger perception of hotter temperatures for those that do  
292 not or rarely go fishing.

293 We further examined the perception reports by analysing the results compiled by site,  
294 i.e., considering the spatial distribution and the main type of economic activity. At site level, it is  
295 also possible to compare perceptions with estimates of rainfall trends. Thus, in the following  
296 sections, we focus on the reports of rainfall (frequency, intensity, displacement of rainy season),  
297 per site.

298

299 *3.3 Rainfall trends and perceptions in the Brazilian Amazon*

300

301 Many previous studies have pointed to changes in rainfall across the Amazon (Almeida  
302 et al. 2016; Arvor et al. 2017b; Debortoli et al. 2015; Espinoza et al. 2009). Rainfall trends may  
303 be more or less significant depending on the season and the geographical location, but in  
304 general these studies have pointed towards a shortening of the rainy season, frequently  
305 associated to weaker intensity of precipitation at the beginning of the season (Debortoli et al.  
306 2015; Dubreuil et al. 2012). We re-examined the reports of rainfall changes (compiled for all  
307 sites in Table 2), including spatial perspective. For example, Figure 3 shows that perceptions of  
308 rainy/dry season changes (question (i)) are clearly heterogeneous across sites: six sites (Chico  
309 Mendes, Oyapock, Parauapebas, Ouro Preto do Oeste, Mamiraua, Juína and Tupé) presented a  
310 40% or higher rate of changes in both rainy and dry seasons. To a lesser degree, this response  
311 was seen in populations in Moikarako, Sorriso and Iratapuru (33%, 21% and 24% respectively).  
312 In the latter sites, the strongest response was that changes in climate have been neither  
313 observed nor felt (49%, 29%, and 43%, respectively). Finally, only two sites reported a higher  
314 rate of perception of changes in the rainy season only, namely Ciriaco (37%) and to a lesser  
315 degree Carlinda.

316 Next, we focused on the observed rainfall trends at each of the 13 sites. Table 8 shows  
317 linear trends based on PERSIANN-CDR data, along with its 95% confidence interval. All trends  
318 show large uncertainty in trend estimates, reflecting the strong interannual rainfall variability  
319 across the entire Amazon region. In the northern part, trends tend to be positive (Mamiraua,  
320 Parauapebas, Moikarako), while they tend to be negative in the southern part (Carlinda, Chico  
321 Mendes and Juína). The linear trends presented in Table 8 reflect the long-term changes in  
322 annual totals, but in order to have a more complete assessment of rainfall pattern changes, we  
323 also examined the trends of mean daily rainfall and number of days with rain based on  
324 PERSIANN-CDR data (Figure 4). This provides further insight. Should rainfall totals increase, it  
325 could be from temporal spreading, indicating a reduced or constant intensity, or it could be  
326 concentrated in lesser number of days, indicating more intense rainfall.

327 Figure 4 shows that Ciriaco appears as the only site where rainfall intensity increases  
328 (decrease of rainfall days with increase in the mean daily rainfall). This is in line with the small  
329 (though not statistically significant) annual total trends. Some sites in the southern and eastern  
330 Amazon showed an increase in the mean daily rainfall and a decrease (or stability) of number of  
331 days with rain in the year. Mamiraua is the only site where the mean daily rainfall and number  
332 of days with rain in the year increased - consistent with the positive trends found for the annual  
333 totals. At many sites, trends in rainfall frequency and intensity are either weak or diametrically  
334 opposed, which explains the weak trends in the annual totals.

335 In addition to estimates of rainfall trends, Table 8 summarizes for each research site the  
336 proportion of each answer to question (ii) (Section 2.1). The most frequent answers point to a  
337 decreasing frequency in rainfall (14.8%), an increase in both the intensity (11.2%) and  
338 unpredictability (14.3%). On average, 10.2% perceive a displacement of either the beginning or  
339 the end of the rainy season. However, an equivalent proportion of the population (9.9%) did not  
340 observe any changes in precipitation patterns. These contrasting results further exemplify the  
341 disparity of perceptions concerning changes in precipitation.

342 The displacement of the rainy season is a striking perception despite not being the most  
343 mentioned. Certain sites referred to the displacement of the rainy season more than others  
344 (Figure 5), for example Ciriaco at above 34%, PAE Chico Mendes at 18%, and more than 10% in  
345 Juína, Oyapock, Moikarako, and Sorriso. The spatial distribution of these responses shows that it  
346 is more perceived in the south, but there is no apparent link with the type of activity  
347 (agribusiness, traditional or indigenous).

348 How well do these perceptions correspond to those estimated by physical  
349 measurements? We found no significant correlation between rainfall trends and any perception  
350 (Table 8), nor between the magnitude or amplitude of interannual variability and perceptions of  
351 rainfall changes (not shown). This result is in line with the bivariate analysis previously shown  
352 which suggested no link between personal sensibility or exposure to the environment and  
353 perceptions of climate change. Nevertheless, an analysis of satellite-based estimates and

354 perceptions shows that, although there is no linear relationship between changes in rainfall  
355 amounts and perceptions, they are qualitatively congruent in most of the study sites with  
356 respect to trends in intensity of rainfall (Figures 2 and 6). Six sites present similar trends  
357 between observed and perceived data: increasing intensity at Iratapuru, Chico Mendes,  
358 decreasing at Ouro Preto do Oeste and no changes at Parauapebas, Moikarako and Sorriso. Only  
359 at Juína were the results somewhat disparate, with positive rainfall intensity trends detected by  
360 PERSIANN-CDR, but lower frequency revealed by the interviews; this is also the only site where  
361 the respondents answered that the rain frequency decreased but with increased intensity.

362 An approximate three-zone spatial arrangement can be discerned (Figure 6):

363

364 – The communities of Oyapock, Iratapuru, Tupé and PAE Chico Mendes (in the north and  
365 western parts of the domain) present notions of increasing trends in precipitation, in volume or  
366 intensity, or both. These perceptions do not match trends based on rainfall observations. In  
367 Mamiraua, no trends in rainfall frequency or intensity were perceived, while a slight increase in  
368 rain frequency has been detected.

369 – Ouro Preto do Oeste, Juína and Carlinda (in the southern part) showed perceptions of  
370 decreasing rainfall. A rather consistent match between perception and observations appears for  
371 the sites of Sorriso (no trends overall), Juína and Carlinda (less rainfall).

372 – Sites located in the eastern Amazon (Anapu, Ciriaco, Parauapebas, Moikarako) show strong  
373 disparity between perceptions and measurement-based estimates regarding both intensity and  
374 total rainfall trends.

375

376 Finally, the unpredictability of rainfall is mentioned by nearly all interviewees, albeit in  
377 different degrees. Oyapock and Mamiraua are the sites in which this aspect was the most  
378 strongly mentioned (37.0 and 31.6%, respectively), followed by Ouro Preto do Oeste (22.8%)  
379 and PAE Chico Mendes (24.5%). Figure 6 indicates that the unpredictability aspect does not

380 present a spatial coherence or preference, nor does it coincide with frequency or intensity of  
381 rainfall.

382

### 383 *3.4 Temporal changes in perceptions*

384

385 Perceptions of climate change in the Amazon were first addressed in the DURAMAZ  
386 project, but it was done on a narrower scope than in its second phase. Except for Oyapock and  
387 Carlinda, the study sites were the same in the two projects. Results of the first phase indicated  
388 that perceptions of changes in climate were varied across the sites, and consistency with the  
389 measured data was not always good. This general result persisted in the second DURAMAZ  
390 phase.

391 All sites indicated most frequently a warmer climate, consistent with previous responses  
392 to questionnaires undertaken 5 years earlier. The most striking element in “open answers” back  
393 in the first data collection was the increase of the irregularity (or unpredictability) of rainfall.  
394 This perception is still a salient result in the DURAMAZ-2 project. Both agricultural-based and  
395 traditional communities (that is those that count on fishing, extractivism, and/or family-scale  
396 agriculture) seem primarily sensitive to the interannual variability of rainfall. The arc of  
397 deforestation in the southern Brazilian Amazon clearly shows a concurrence of lower rainfall  
398 and higher perception of rainfall change by communities. This feature persisted into the second  
399 phase of the DURAMAZ project and is particularly noteworthy as the 2013-2014 rainy season  
400 was locally wetter than in 2008-2009. The most relevant difference with respect to the earlier  
401 finding was that comments on global warming were spontaneously brought up among the  
402 interviewees (included in response “Others”), indicating a heightened climate change  
403 awareness.

404

### 405 *3.5 Connections between agricultural practices and climate observations and perceptions*

406



407 The agricultural calendars in the Amazon are primarily based on meteorological (rainfall  
408 regimes) and/or hydrological (river levels) seasonality. Even though no relationship between  
409 changes in activity and climate change perceptions appeared in the bivariate analysis, a site-  
410 dependent relevant signal could still exist. In the southern Amazon, the soil is prepared during  
411 the dry season (June through August) and seeding begins with the start of the rainy season  
412 (September through November; Arvor et al. 2014). Perceptions of climate change are especially  
413 relevant in this context as it may influence cropping practices adopted by these communities.  
414 During the interviews, the respondents were invited to explain their agricultural planning and  
415 practices and then their motivation for each decision, without invoking a priori any climatic  
416 forcing. For this question, it is possible that the level of experience of the interviewer had an  
417 imprint on the results.

418 Figure 7 shows that, before sowing, the crop calendar is mainly based on the observation  
419 of climate (knowledge of astronomical cycles, seasonal rhythm of precipitation, blossoming;  
420 20%) and on ancestral knowledge (practice of particular rituals; 22%). This traditional way of  
421 working was particularly prominent in Ciriaco, Parauapebas, PAE Chico Mendes, Ouro Preto and  
422 Iratapuru. In other sites, traditional knowledge and observations are combined with more  
423 modern technical means, such as the monitoring of weather forecasts on radio or television  
424 (Ouro Preto, Chico Mendes, Oyapock, Parauapebas, Juína, Sorriso). At Sorriso, producers follow  
425 a distinct, technical procedure relying on in-situ rain gauge measurements: soybean seeding  
426 starts after an average of 70-80 mm of accumulated rainfall (Arvor et al. 2014). In this case, the  
427 harvest is also decided by an agronomical analysis of the degree of maturity of the grains.

428 Changes in recent practices or types of production related to climatic changes were  
429 reported only in the Mato Grosso state (38.9% of total answers) and correspond to a better  
430 adaptation to environmental conditions. For example, several producers in Juína began to  
431 irrigate their plots to secure the production and make it effective throughout the year. In  
432 Carlinda, conversion from agriculture to dairy production led livestock farmers to try to cushion  
433 the decline in production (and hence the loss of income) during the dry season by developing

434 water reservoirs or by supplementing fodder crops from May to September. In Sorriso, there  
435 was a general replacement of single seeding to the dual-cropping (“safra-safrinha”) system  
436 aiming at extending land productivity throughout the rainy season (Arvor et al. 2014). Lastly,  
437 there was an increase in the practice of irrigation at the beginning of the dry season for certain  
438 crops (e.g., beans; Arvor et al. 2018). These examples attest to efforts to adapt farming practices  
439 according to perceived changes in climate. The main motivation though is economic rather than  
440 for environmental awareness reasons.

441

#### 442 **4 Discussion and Final Remarks**

443

444 Climate variations in the Amazon basin are recognized as approaching a tipping point  
445 (Lovejoy and Nobre 2018). Since the mid-2000s until ~2012, the rates of deforestation have  
446 decreased (e.g., Nobre et al. 2016) and Brazil committed to the sustainable development goals  
447 and resolutions agreed upon during the United Nations Conference on Sustainable Development  
448 (Rio+20) in 2012. However, recent political decisions in the country have signalled an end to  
449 these commitments and a pull-out from the 2015 Paris Climate Agreement. Deforestation is now  
450 officially endorsed by the Brazilian government (Rochedo et al. 2018) and has reached a peak  
451 7900 km<sup>2</sup> in July 2018 as estimated by the Brazilian National Institute for Space Research  
452 (INPE). This decision is diametrically opposed to the latest IPCC recommendations (IPCC 2018)  
453 for sustainable forest management to contain global warming at 1.5°C and support other  
454 sustainability goals such as securing food, clean water and environmental protection.

455 As scientists aim at quantifying climate change – arguably to render it “visible” (e.g.,  
456 Rudiak-Gould 2013) - people at the frontline of deforestation and land cover changes in the  
457 Amazon region have their own perceptions of change. Generally, comparing physical quantities  
458 with social data on perceptions is delicate, as it may lead to a hierarchical reading between “the  
459 true nature” whose study is an attribute of natural scientists, and the “culturally constructed”  
460 nature, whose study is an attribute of social scientists (Brondizio and Moran 2008; Ingold 2000;

461 Morton 2007, Swim et al. 2009, Rudiak-Gould 2013). However, introducing a “subjective”  
462 dimension in vulnerability analysis is important: the metrics of the natural sciences are  
463 fundamental to define, calculate and predict climate change, but are not sufficient to establish  
464 strategies on how to address the problems, especially at the local level. As such, we aimed at  
465 comparing and contrasting independent, measured data against perceptions and examined  
466 possible links that could explain a given notion of change.

467 About 72% of the sampled population (N = 1271) perceived changes in climate. A  
468 statistically robust increase in perception of change with age was found, congruent with the  
469 “shifted baseline” concept (Hansen et al. 2011). This increased perception with age was also  
470 found by e.g., Rudiak-Gould (2014) and Alessa et al. (2008) who studied indigenous and native  
471 communities in the Marshall Islands and in the Seward Peninsula (Alaska), respectively. On the  
472 other hand, climate change perception studies for New Zealand and for European countries have  
473 shown that older age groups, particularly those with fewer years of formal education, tend to  
474 acknowledge to a lesser degree the existence and anthropogenic nature of climate change  
475 (Poortinga et al. 2011, 2019, Milfont et al. 2015). Moreover, in these latter areas, men were more  
476 likely to doubt climate change than women, whereas in rural Amazonia gender did not appear as  
477 a significant factor to explain reports of climate change (also reported by Alessa et al. 2008).

478 Other factors such as environmental exposure (fishing) and personal experience (change  
479 in activity, agricultural planning, weather forecasting) also did not appear to affect perception  
480 reports. A similar finding was documented by Rudiak-Gould (2014). However, studies  
481 conducted with communities in the Arctic region indicate increased climate change perceptions  
482 with environmental exposure and with the transmission of traditional knowledge by the elders  
483 (e.g., Riedlinger and Berkes 2001, Furgal and Seguin 2006, Alessa et al. 2008, Wolf and Moser  
484 2011). In the Arctic region, the notion of “visibility” of climate change takes full meaning as the  
485 Arctic is a hot spot of vulnerability to climate change (Giorgi 2006) and environmental changes  
486 can be more “visible” – for example the sensible reduction in the seasonal extent and

487 distribution of sea ice, wildlife abundance and health, permafrost thaw – compared to changes  
488 in the tropical regions.

489         The reports gathered in this current study show that about 19% of the interviewees  
490 spontaneously mentioned deforestation as a possible driver of local climate change. Indeed,  
491 deforestation has the potential to decrease evapotranspiration rates and increase in local  
492 temperature, which coincides with perceptions of hotter (7.6%) and drier (1%) climate.  
493 Changes in temperature and humidity can in turn lead to changes in local precipitation patterns.  
494 In this study, satellite-based estimates of rainfall trends at 13 sites across the Amazon basin  
495 show more positive trends in its central and northern parts than in the south, while the eastern  
496 part show inconclusive trends, though pointing towards an increase in the intensity. Even if  
497 such trends are weak, there has been mounting evidence that the Amazon region ecosystem is  
498 transitioning to a disturbance-dominated regime, particularly in the southern and eastern parts  
499 of the basin.

500         We further analysed the results by the geographical location of sites. No robust  
501 correlation was found between perceptions and the quantitative value of the trends, nor its  
502 intensity or variation. Nevertheless, in the southern part of the Brazilian Amazon, there is an  
503 overlap between a measured reduction in precipitation and a strong perception in rainfall  
504 changes by the local communities. This perception is persistent throughout at least 5 years, as it  
505 was first detected during the first DURAMAZ project. Other steady perceptions are that of  
506 displacement of the rainy season and increasing irregularity (or unpredictability) of rain. The  
507 overlap between observed and perceived reduction in precipitation and/or displacement of the  
508 rainy season is indeed remarkable as it appears despite possible bias of respondents to the  
509 questionnaires. Some respondents were potentially uneasy saying that rainfall patterns were  
510 changing for fear that this could be asserting a linkage to deforestation, even though the term  
511 “deforestation” did not appear anywhere in the questionnaires.

512         This study went beyond still by looking at the connections between agricultural  
513 practices and climate calendar. Economic activities with links to rainfall are sensitive to its

514 interannual variability and extreme events. However, for some sites, crop planning is linked to  
515 market prices and thus can evolve dynamically to remain competitive in the market. The  
516 production of the most lucrative products is favoured, particularly at the Sorriso and Ciriaco  
517 sites. Adaptation to climate variations is more frequently observed within the agricultural  
518 communities in the south (e.g., Sorriso and Juína): in order to adapt to the constraints of rainfall  
519 fluctuations, irrigation has become more frequent in the Amazon. Artificial ponds, created on  
520 river networks to ensure water supply for maize and cotton crops, have multiplied across the  
521 southeastern agricultural frontier (Arvor et al., 2018), raising questions on the potential  
522 negative effects on hydrology, biodiversity, geochemistry of soils and global warming across  
523 temporal and spatial scales. Other adaptive measures, seen at Juína, include the abandon of a  
524 crop, change of crop, alterations in the seeding date and implementation of greenhouses.

525 Perceptions of climate change alone will hardly lead to action as economic (market  
526 dynamics) and political forces constitute the main constraints for behaviour change (Weber  
527 2006, 2010, Wolf and Moser 2011, Nobre et al. 2016, Bakaki and Bernauer 2017, Rochedo et al.  
528 2018, Arvor et al. 2017a, Hamilton 2018, Poortinga et al. 2019). Nevertheless, this study pointed  
529 out that a higher awareness of the changing climate is emerging within Amazonian  
530 communities. Even if still modest, an increase in climate risk perception has the potential to  
531 influence the adoption of measures that aim to a better relationship between humans and their  
532 surrounding environment.

533

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791

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793 “DK/DA” denotes “don’t know/didn’t answer”.

794

795 **Table 3** Bivariate analysis: gender vs perception reports. All values were found to be significant  
796 at 95% level when tested against a binomial distribution (2-tailed test), with the null hypothesis  
797 being an equal chance of getting a yes/no answer to each perception question.

798

799 **Table 4** Bivariate analysis: age vs perception reports. Values in bold are significant at 95% level  
800 when tested against a binomial distribution (2-tailed test), with the null hypothesis being a  
801 random, equal chance of getting a yes/no answer to each perception question. Spearman rank-  
802 order correlation coefficient ( $r_s$ ) refers to the correlation between the increase in age and % of  
803 report in climate change, and  $\sigma$  is the corresponding 2-sided significance. Values in bold  
804 correspond to statistically significant values at the 95% level.

805

806 **Table 5** Bivariate analysis: Fishing frequency vs perception reports. “DK/DA” denotes “don’t  
807 know/didn’t answer”. Values in bold are significant at 95% level when tested against a binomial  
808 distribution (2-tailed test), with the null hypothesis being a random chance of getting a yes/no  
809 answer to each perception question. Spearman rank-order correlation coefficient ( $r_s$ ) refers to  
810 the correlation between the increase in fishing frequency (values for “DK/DA” and “Irregularly”  
811 were not considered) and % of report in climate change. Kendall rank correlation coefficient ( $\tau$ )  
812 was calculated to examine whether the percentage of report in climate change was influenced  
813 by the irregular sample size, and  $\sigma$  is their associated 2-sided significance. Values in bold  
814 correspond to statistically significant correlation at the 95% level.

815

816 **Table 6** Bivariate analysis: Changes in activity in the last 3 years vs perception reports. “DK/DA”  
817 denotes “don’t know/didn’t answer”. Values in bold are significant at 95% level when tested  
818 against a binomial distribution (2-tailed test), with the null hypothesis being a random chance of  
819 getting a yes/no answer to each perception question. Kendall rank correlation coefficient ( $\tau$ )  
820 was calculated to examine whether the % of report in climate change was influenced by the  
821 irregular sample size;  $\sigma$  is the corresponding 2-sided significance.

822

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824 bold are significant at 95% level when tested against a binomial distribution (2-tailed test), with  
825 the null hypothesis being a random chance of getting a yes/no answer to each perception  
826 question. Kendall rank correlation coefficient ( $\tau$ ) was calculated to examine whether the % of

827 report in climate change was influenced by the irregular sample size;  $\sigma$  is the corresponding 2-  
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829

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831 based on PERSIANN-CDR estimates at the nearest grid point to the DURAMAZ-2 site. Perception  
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833 represents the percentage of answers to the question (ii) (Section 2.1) “Since the event  $x$ , which  
834 changes did you notice?”. The respondents could choose multiple answers. Spearman rank-  
835 order correlation coefficient ( $r_s$ ) refers to the correlation between linear trends and percentage  
836 of each reported change;  $\sigma$  is the corresponding 2-sided significance.

837

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839

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842 available.

843

844 **Fig. 2** Synthetic chart of methodology process for obtaining first the independent variables  
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846 in this study. “Multi-option” answers denote closed-type questions (unless the option “Other,  
847 elaborate” was given), unlike “Open answer”, where the answer was later decoded to group  
848 similar answers. See text for details.

849

850 **Fig. 3** Percentage of population for each study site that observed changes both in the dry and  
851 rainy seasons, or that did not observe any changes.

852

853 **Fig. 4** Mean daily rainfall (black), and total number of days with rain (gray), based on  
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857

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860

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863 **Fig. 7** Percentage of three types of responses given to the question “How do you plan your  
864 cultures?”

865 **Table 1** Name (locality and state), geographical coordinates (shown in Figure 1), and basic  
 866 characteristics of the DURAMAZ-2 study sites.  
 867

DURAMAZ-2 site	Geogr. Coord. Lat °N/Lon °E	Main economic activity	Deforested area (2012)	Number of interviewed households & average number of children per family
Oyapock (AP)	3.84 / -51.83	Fishing	18%	80 / 4.2
Iratapuru (PA)	-0.57 / -52.58	Extractivism (Brazil nut), fishing, hunting	0.1%	36 / 5.3
Mamiraua (AM)	-2.29 / -65.85	Extractivism / Ecotourism	0 %	40 / 3.5
Tupé (AM)	-3.00 / -60.25	Extractivism / Ecotourism	25 %	36 / 4.0
Anapu (PA)	-3.79 / -51.33	Small-scale agriculture	16 %	68 / 3.6
Ciriaco (MA)	-5.27 / -47.79	Extractivism (babaçu nut)	58 %	73 / 4.2
Parauapebas (PA)	-5.97 / -50.22	Small-scale farming	24.7%	43/4.9
Moikarako (PA)	-7.44 / -51.82	Extractivism (Brazil nut)	0.7 %	40 / 3.6
Carlinda (MT)	-10.10 / -55.76	Small-scale farming	89.2 %	52 / 1.2
Ouro Preto do Oeste (RO)	-10.74 / -62.22	Small-scale farming	33.5%	81 / 3.4
PAE Chico Mendes (AC)	-10.84 / -68.38	Extractivism of forest products	10.2%	70 / 3.3
Juína (MT)	-11.42 / -58.74	Small-scale farming	99.7%	74 / 3.3
Sorriso (MT)	-12.39 / -55.81	Agribusiness	71.2%	54 / 1.8

868



869 **Table 2** Univariate analysis of independent variables and perceptions (outcome variables).  
 870 “DK/DA” denotes “don’t know/didn’t answer”.  
 871

Independent Variables	N (%)	Outcome Variables	N = 1271 (%)
Age (years)	1244	Reports rainy/dry season changes	
0-20 .....	142 (11.4)	No .....	466 (36.7)
21-25 .....	129 (10.4)	Yes .....	805(63.3)
26-30 .....	127 (10.2)	Dry and wet season .....	470 (37.0)
31-35 .....	149 (12.0)	Only wet season .....	232 (18.3)
36-40 .....	130 (10.4)	Only dry season .....	103 (8.1)
41-45 .....	112 (9.0)		
46-50 .....	104 (8.4)	Reports climate changes other	
51-55 .....	107 (8.6)	than rainfall	
56-60 .....	92 (7.4)	No .....	423 (33.3)
61+ .....	152 (12.2)	Yes .....	161 (12.7)
Gender	1267	Hotter .....	96 (7.6)
Male .....	673 (53.1)	Drier .....	13 (1.0)
Female .....	594 (46.9)	Windier .....	11 (0.9)
Frequency of fishing	702	Weather extremes (drought,	
Never .....	254 (36.2)	flood) .....	37 (2.9)
DK/DA .....	20 (2.9)	Temperature changes .....	4 (0.3)
≤ 1x/year .....	29 (4.1)		
1x/3mo .....	31 (4.4)	Reports changes in rainfall	
1x/mo .....	72 (10.0)	No .....	423 (33.3)
1x/15days .....	40 (5.7)	Yes .....	848 (66.7)
1x/week .....	89 (12.7)	Intensity .....	354 (27.9)
≥ 2x/week .....	82 (11.7)	Frequency .....	359 (28.3)
Irregularly .....	86 (12.3)	Unpredictability .....	245 (19.3)
Changes in activity in the		Suggests driver of climate change	
last 3 years	702	Didn't answer .....	557 (43.8)
No .....	100 (14.2)	Don't know .....	185 (14.6)
Seeding time .....	59 (8.4)	Non-anthropogenic .....	187 (14.7)
Abandoned a crop or		Anthropogenic forcing .....	392 (30.8)
culture .....	88 (12.5)	Deforestation .....	245 (19.3)
Started new culture(s)		Dam building .....	65(5.1)
.....	51 (7.3)	Environmental/soil	
Changes in livestock		degradation .....	33 (2.6)
farming .....	7 (1)	Other (cattle, fire, road, etc.) .....	49 (3.9)
Others .....	67 (9.5)		
DK/DA .....	330 (46.9)		
Weather forecasting	702		
Does not use/care ....	48 (6.8)		
TV/radio/etc .....	43 (6.1)		
Experience .....	177 (25.2)		
Combination of			
information and			
experience .....	20 (2.9)		
DK/DA .....	414 (59)		

872 **Table 3** Bivariate analysis: gender vs perception reports. All values were found to be significant  
 873 at 95% level when tested against a binomial distribution (2-tailed test), with the null hypothesis  
 874 being a random, equal chance of getting a yes/no answer to each perception question.  
 875

	Sample size	Reports climate change (in general)	Reports rain/dry season changes	Reports changes other than rain	Reports changes rainfall patterns	Suggests human driver of climate change
Gender	N	N (%)	N (%)	N (%)	N (%)	N (%)
Male	673	476 (70.7)	420 (62.4)	73 (10.8)	362 (53.8)	194 (28.8)
Female	594	434 (73.0)	383 (64.5)	71 (12.0)	337 (56.7)	145 (24.4)
TOTAL	1267	910 (71.8)	803 (63.4)	144 (11.4)	699 (52.8)	339 (26.8)

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881 **Table 4** Bivariate analysis: age vs perception reports. Values in bold are significant at 95% level  
 882 when tested against a binomial distribution (2-tailed test), with the null hypothesis being a  
 883 random chance of getting a yes/no answer to each perception question. Spearman rank-order  
 884 correlation coefficient ( $r_s$ ) refers to the correlation between the increase in age and % of report  
 885 in climate change, and  $\sigma$  is the corresponding 2-sided significance. Values in bold correspond to  
 886 statistically significant values at the 95% level.

	Sample size	Reports climate change (in general)	Reports rain/dry season changes	Reports changes other than rain	Reports changes rainfall patterns	Suggests human driver of climate change
Age	N	N (%)	N (%)	N (%)	N (%)	N (%)
0-20	144	<b>88 (62.0)</b>	74 (52.1)	<b>12 (8.5)</b>	<b>58 (40.8)</b>	<b>37 (26.1)</b>
21-25	129	<b>81 (62.8)</b>	75 (58.1)	<b>14 (10.9)</b>	58 (45.0)	<b>36 (27.9)</b>
26-30	127	<b>86 (67.7)</b>	<b>77 (60.6)</b>	<b>15 (11.8)</b>	59 (46.5)	<b>35 (27.6)</b>
31-35	149	<b>110 (73.8)</b>	<b>98 (65.8)</b>	<b>13 (8.7)</b>	82 (55.0)	<b>42 (28.2)</b>
36-40	130	<b>94 (72.3)</b>	<b>88 (67.7)</b>	<b>15 (11.6)</b>	68 (52.3)	<b>36 (27.7)</b>
41-45	112	<b>80 (71.4)</b>	<b>72 (64.3)</b>	<b>12 (10.7)</b>	58 (51.8)	<b>27 (24.1)</b>
46-50	104	<b>82 (78.8)</b>	<b>69 (66.3)</b>	<b>16 (15.4)</b>	54 (51.9)	<b>31 (29.8)</b>
51-55	107	<b>87 (81.3)</b>	<b>80 (74.8)</b>	<b>23 (21.5)</b>	56 (52.3)	<b>26 (24.3)</b>
56-60	92	<b>77 (83.7)</b>	<b>72 (78.3)</b>	<b>11 (12.0)</b>	49 (53.3)	<b>25 (27.2)</b>
61+	152	<b>108 (71.1)</b>	88 (57.9)	<b>13 (8.6)</b>	<b>60 (39.5)</b>	<b>41 (27.0)</b>
TOTAL	1244	<b>893 (71.8)</b>	<b>793 (63.8)</b>	<b>144 (11.6)</b>	602 (48.5)	<b>336 (27.0)</b>
$r_s$ ( $\sigma$ )		<b>0.70 (0.03)</b>	0.50 (0.14)	0.37 (0.3)	0.24 (0.5)	-0.21 (0.56)

887

888 **Table 5** Bivariate analysis: Fishing frequency vs perception reports. “DK/DA” denotes “don’t  
 889 know/didn’t answer”. Values in bold are significant at 95% level when tested against a binomial  
 890 distribution (2-tailed test), with the null hypothesis being a random chance of getting a yes/no  
 891 answer to each perception question. Spearman rank-order correlation coefficient ( $r_s$ ) refers to  
 892 the correlation between the increase in fishing frequency (values for “DK/DA” and “Irregularly”  
 893 were not considered) and % of report in climate change. Kendall rank correlation coefficient ( $\tau$ )  
 894 was calculated to examine whether the percentage of report in climate change was influenced  
 895 by the irregular sample size. and  $\sigma$  is their associated 2-sided significance. Values in bold  
 896 correspond to statistically significant correlation at the 95% level.  
 897

	Sample size	Reports climate change (in general)	Reports rain/dry season changes	Reports changes other than rain	Reports changes rainfall patterns	Suggests human driver of climate change
Fishing freq	N	N (%)	N (%)	N (%)	N (%)	N (%)
Never	252	<b>185 (73.4)</b>	<b>157 (62.3)</b>	<b>51 (20.2)</b>	<b>197 (78.2)</b>	<b>65 (26.0)</b>
DK/DA	19	<b>15 (78.9)</b>	10 (52.6)	<b>1 (5.3)</b>	<b>18 (94.7)</b>	6 (31.6)
≤ 1x/year	29	<b>26 (89.7)</b>	<b>25 (86.2)</b>	<b>6 (20.7)</b>	<b>26 (89.7)</b>	<b>8 (26.7)</b>
1x/3mo	31	19 (61.3)	18 (58.1)	5 (16.1)	14 (45.2)	7 (21.9)
1x/mo	71	<b>55 (77.5)</b>	<b>49 (69.0)</b>	<b>8 (11.3)</b>	<b>70 (98.6)</b>	29 (41.4)
1x/15days	39	31 (79.5)	30 (76.9)	7 (18.0)	38 (97.4)	14 (35.9)
1x/week	87	<b>66 (75.9)</b>	<b>62 (71.3)</b>	<b>13 (14.9)</b>	<b>71 (81.6)</b>	<b>27 (31.0)</b>
≥ 2x/week	81	<b>52 (64.2)</b>	48 (59.3)	<b>8 (9.9)</b>	<b>51 (63.0)</b>	<b>15 (18.5)</b>
Irregularly	86	<b>65 (75.6)</b>	<b>59 (68.6)</b>	<b>15 (17.4)</b>	<b>78 (90.7)</b>	<b>25 (28.7)</b>
TOTAL	695	<b>514 (74.0)</b>	<b>458 (65.9)</b>	<b>114 (16.4)</b>	<b>563 (81.0)</b>	<b>196 (28.2)</b>
$r_s$ ( $\sigma$ )		-0.1 (0.8)	-0.1 (0.9)	<b>-0.8 (0.04)</b>	0 (1.0)	0 (1.0)
$\tau$ ( $\sigma$ )		-0.3 (0.2)	0.1 (0.8)	0.1 (0.7)	-0.2 (0.5)	-0.1 (0.6)

898

899 **Table 6** Bivariate analysis: Changes in activity in the last 3 years vs perception reports. “DK/DA”  
 900 denotes “don’t know/didn’t answer”. Values in bold are significant at 95% level when tested  
 901 against a binomial distribution (2-tailed test), with the null hypothesis being a random chance of  
 902 getting a yes/no answer to each perception question. Kendall rank correlation coefficient ( $\tau$ )  
 903 was calculated to examine whether the % of report in climate change was influenced by the  
 904 irregular sample size;  $\sigma$  is the corresponding 2-sided significance.

905

	Sample size	Reports climate change (in general)	Reports rain/dry season changes	Reports changes other than rain	Reports changes rainfall patterns	Suggests human driver of climate change
Changes in the last 3 yrs	N	N (%)	N (%)	N (%)	N (%)	N (%)
No changes	85	<b>63 (74.1)</b>	<b>61 (71.8)</b>	<b>26 (30.6)</b>	<b>80 (94.1)</b>	<b>27 (31.4)</b>
Seeding time	51	<b>45 (88.2)</b>	<b>40 (78.4)</b>	<b>7 (13.7)</b>	<b>44 (86.3)</b>	<b>16 (31.4)</b>
Abandoned crop/culture	82	<b>62 (75.6)</b>	<b>55 (67.1)</b>	<b>17 (20.7)</b>	<b>61 (74.4)</b>	35 (42.2)
Started new culture	43	26 (60.5)	24 (55.8)	<b>8 (18.6)</b>	<b>29 (67.4)</b>	18 (41.9)
Livestock	6	3 (50.0)	3 (50.0)	3 (50.0)	1 (16.7)	1 (16.7)
Other	66	<b>52 (78.8)</b>	<b>51 (30.3)</b>	<b>20 (30.3)</b>	<b>55 (83.3)</b>	30 (46.2)
DK/DA	296	<b>224 (75.7)</b>	<b>185 (83.3)</b>	<b>29 (9.8)</b>	<b>227 (76.7)</b>	<b>55 (18.6)</b>
TOTAL	629	<b>475 (75.5)</b>	<b>419 (66.6)</b>	<b>110 (17.5)</b>	<b>497 (78.9)</b>	<b>182 (28.9)</b>
$\tau$ ( $\sigma$ )		0.2 (0.5)	0.1 (0.7)	-0.2 (0.5)	0.4 (0.2)	0.1 (0.9)

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907

908 **Table 7** Bivariate analysis: How do you predict the weather vs perception reports. Values in  
 909 bold are significant at 95% level when tested against a binomial distribution (2-tailed test), with  
 910 the null hypothesis being an equal chance of getting a yes/no answer to each perception  
 911 question. Kendall rank correlation coefficient ( $\tau$ ) was calculated to examine whether the % of  
 912 report in climate change was influenced by the irregular sample size;  $\sigma$  is the corresponding 2-  
 913 sided significance.

914

	Sample size	Reports climate change (in general)	Reports rain/dry season changes	Reports changes other than rain	Reports changes rainfall patterns	Suggests human driver of climate change
Weather forecast	N	N (%)	N (%)	N (%)	N (%)	N (%)
DK/DA	401	<b>279 (69.6)</b>	<b>239 (59.6)</b>	<b>80 (20.0)</b>	<b>305 (76.1)</b>	<b>104 (25.9)</b>
Does not use TV/radio/etc	40	<b>28 (70.0)</b>	26 (65.0)	<b>11 (27.5)</b>	<b>31 (77.5)</b>	<b>9 (22.5)</b>
Life exper.	42	<b>34 (81.0)</b>	<b>29 (69.0)</b>	<b>2 (4.8)</b>	23 (54.8)	15 (35.7)
Comb.of the two above	151	<b>124 (82.1)</b>	<b>115 (76.2)</b>	<b>21 (13.9)</b>	<b>123 (81.5)</b>	<b>48 (31.8)</b>
	19	17 (89.5)	17 (89.5)	0 (0)	15 (78.9)	8 (42.1)
<b>TOTAL</b>	<b>653</b>	<b>482 (73.8)</b>	<b>426 (65.2)</b>	<b>114 (17.5)</b>	<b>497 (76.1)</b>	<b>184 (28.2)</b>
$\tau$ ( $\sigma$ )		-0.4 (0.3)	-0.4 (0.3)	0.4 (0.3)	-0.2 (0.6)	-0.4 (0.3)

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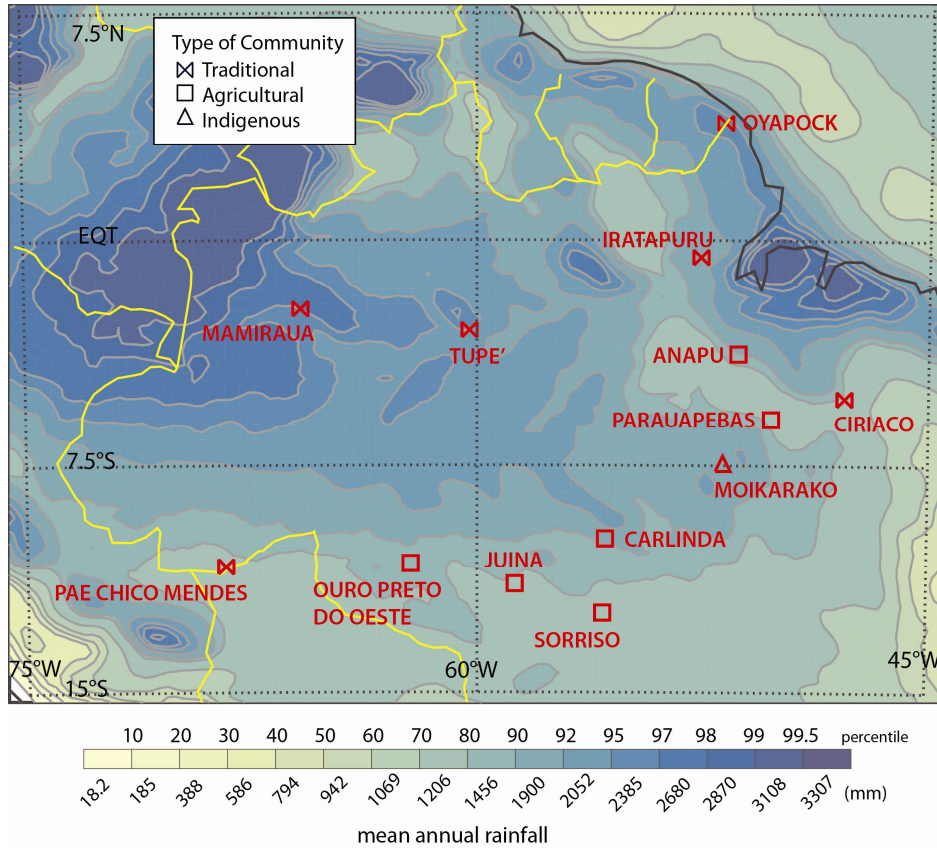
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917 **Table 8** Second column: Linear trends (mm/year) of satellite-derived precipitation estimates at  
 918 the nearest grid point to the DURAMAZ-2 site, for the period 1983-2012, along with the 95%  
 919 confidence interval. Third until last columns: Perceptions of rainfall changes at the Amazonian  
 920 sites studied in the DURAMAZ-2 program. Each column represents the percentage of answers to  
 921 the question (ii) (Section 2.1) “Since the event x, which changes did you notice?”. The  
 922 respondents could choose multiple answers. Spearman rank-order correlation coefficient ( $r_s$ )  
 923 refers to the correlation between linear trends and percentage of each reported change;  $\sigma$  is the  
 924 corresponding 2-sided significance.

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DUR-2 Site	Linear Trends (mm/yr)	Increased rainfall intensity	Decreased rainfall intensity	Rainy season displacement	Unpredictability	Increased rain freq.	Decreased rain freq.	No changes
OYA	-6.2 ± 17.4	3.2	0.0	12.2	37.0	0.0	0.0	37.0
IRA	-4.3 ± 14.1	15.3	2.4	4.7	9.4	14.1	1.2	23.5
MAM	11.8 ± 8.2	15.8	15.8	7.0	31.6	1.8	7.0	7.0
TUP	3.2 ± 10.8	57.8	0.0	8.9	4.4	4.4	9.9	11.1
ANA	1.2 ± 15.9	5.2	30.2	4.1	5.8	8.1	33.1	10.5
CIR	1.8 ± 13.3	5.4	7.2	34.1	9.0	5.4	19.8	5.4
PAR	5.8 ± 11.0	0.0	9.5	3.2	0.0	3.2	6.3	1.6
MOI	5.7 ± 7.6	12.7	21.8	10.9	9.1	1.8	7.3	20.0
CAR	-4.5 ± 8.2	7.7	0.0	5.5	5.5	1.1	19.8	9.9
OUR	1.1 ± 6.3	6.5	19.6	5.4	22.8	7.1	19.0	2.2
PAE	-1.6 ± 7.8	16.6	4.8	18.3	24.5	21.8	5.2	3.5
JUI	-1.3 ± 6.7	13.6	1.8	11.2	10.1	0.6	24.9	8.3
SOR	1.6 ± 7.3	4.9	2.4	12.2	12.2	7.3	7.3	24.4
Average	-	11.2	10.1	10.2	14.3	7.7	14.8	9.9
$r_s$ ( $\sigma$ )		0.0 (0.9)	0.5 (0.06)	-0.2 (0.6)	-0.3 (0.3)	0.0 (1.0)	0.1 (0.7)	-0.3 (0.3)

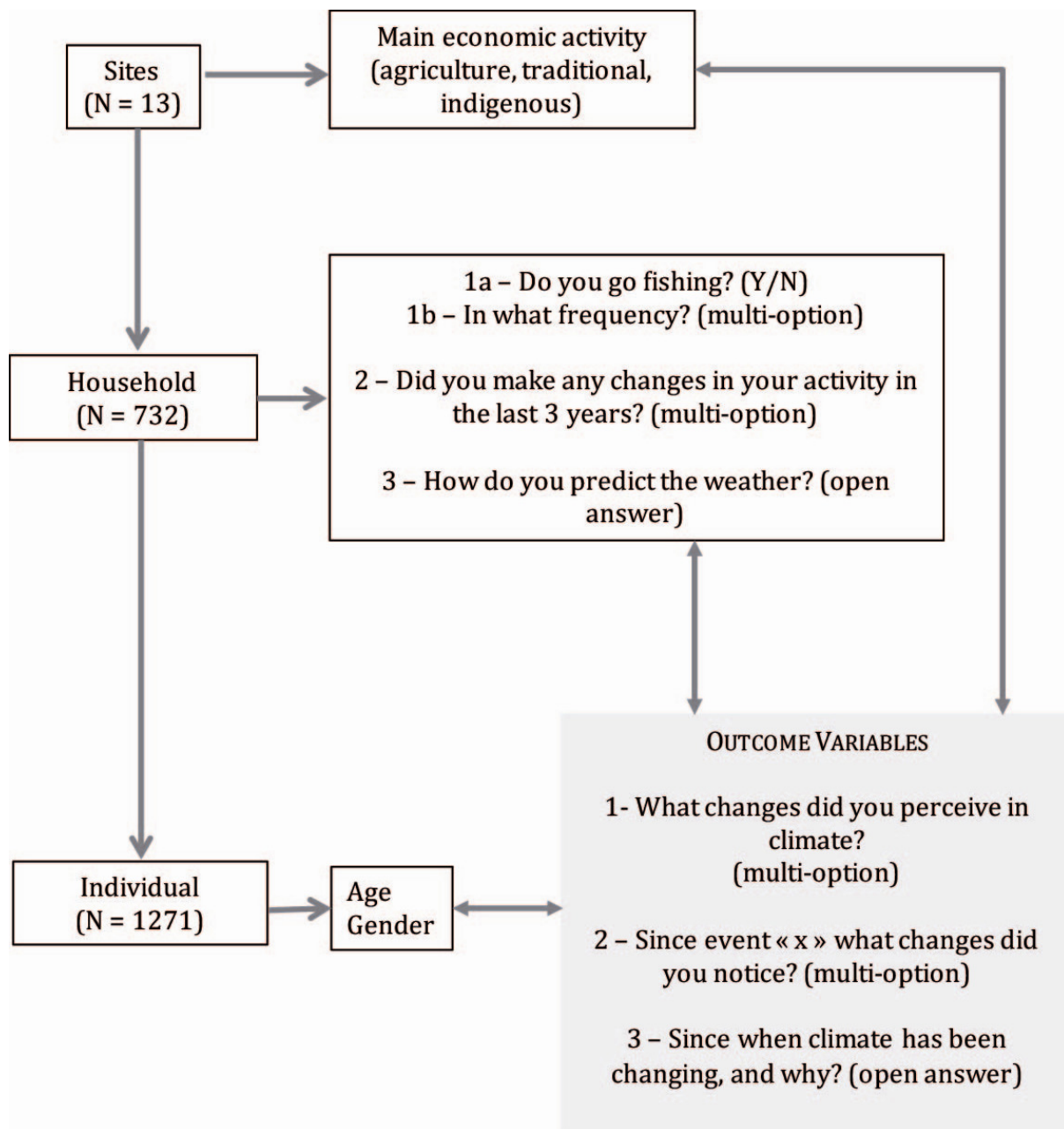
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**Fig. 1** PERSIANN-CDR based mean annual rainfall (1983-2012) in the Amazon region. Red symbols show the study sites. The year 1992 was not included as data for February is not available.

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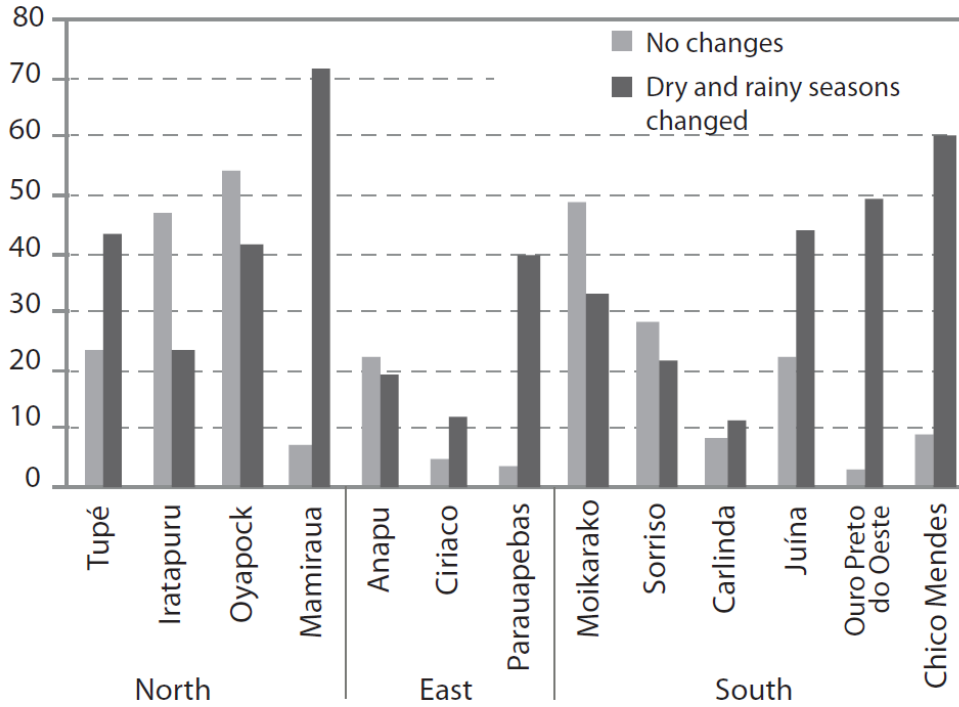


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**Fig. 2** Schematics of methodology process for obtaining first the independent variables (directly connected to each level - sites, household, individual - , and the outcome variables used in this study. “Multi-option” answers denote closed-type questions (unless the option “Other, elaborate” was given), unlike “Open answer”, where the answer was later decoded to group similar answers. See text for details.



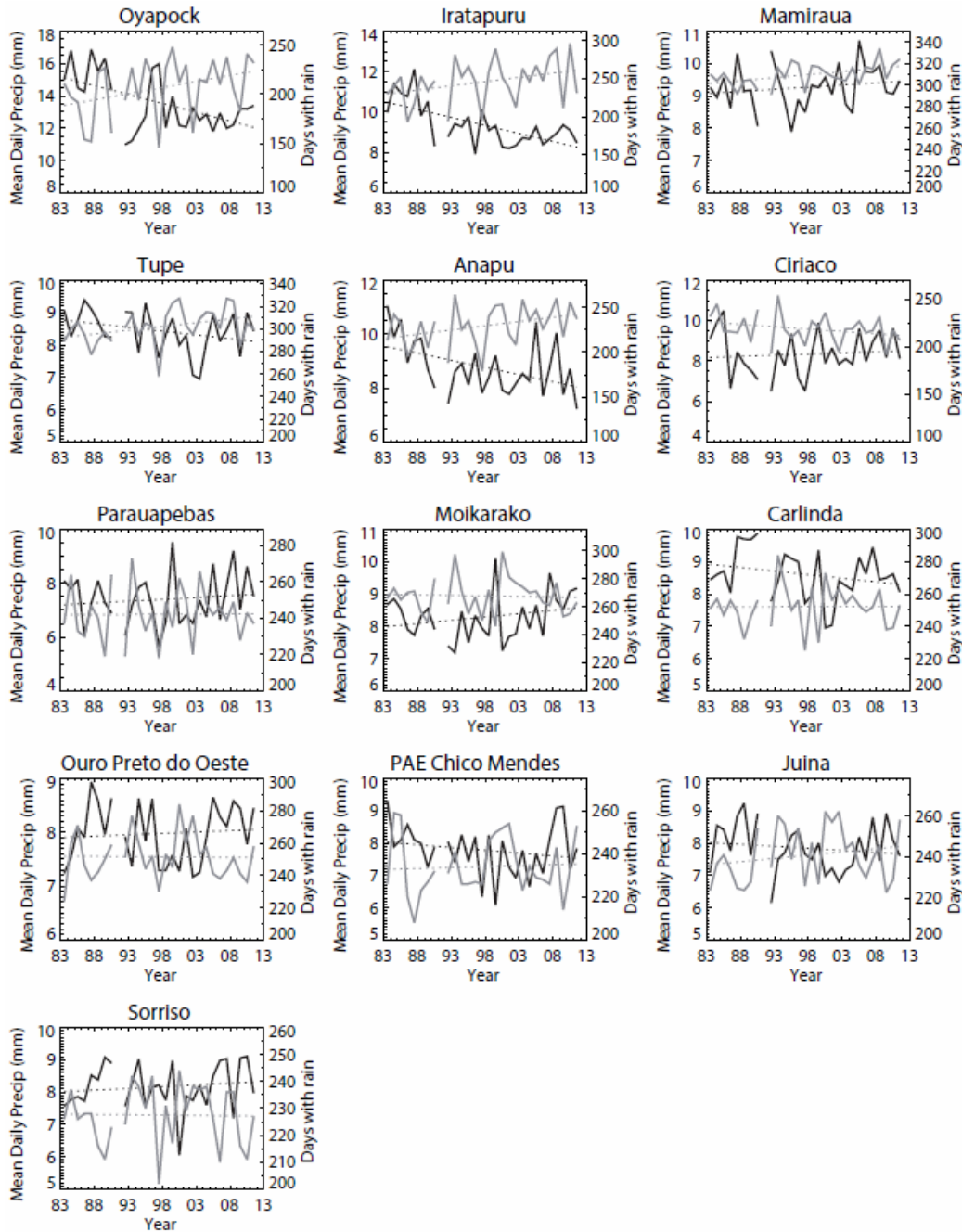
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**Fig. 3** Percentage of population at each site that observed changes both in the dry and rainy seasons, or that did not observe any changes.

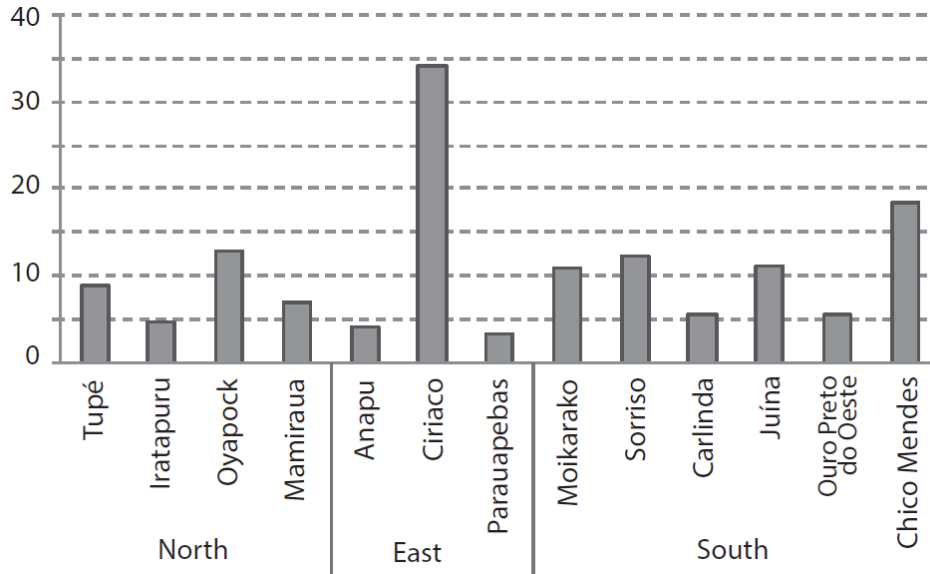
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**Fig. 4** Mean daily rainfall (black), and total number of days with rain (gray), based on PERSIANN-CDR for each DURAMAZ-2 site. Both quantities were counted from July to June the following year. Lines correspond to the linear trend (1983-2012) for each parameter; trends are not statistically significant.

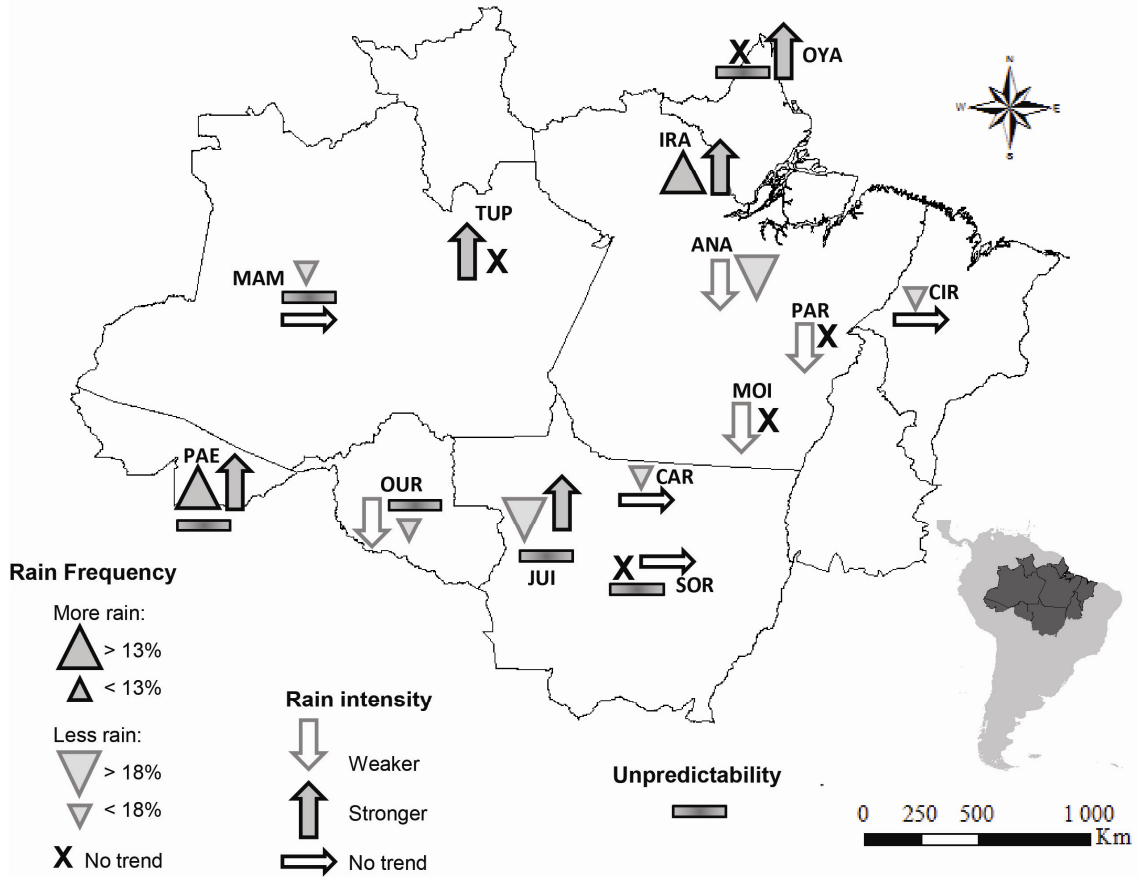
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**Fig. 5** Percentage of answers concerning the perception of displacement of rainy season, per site.

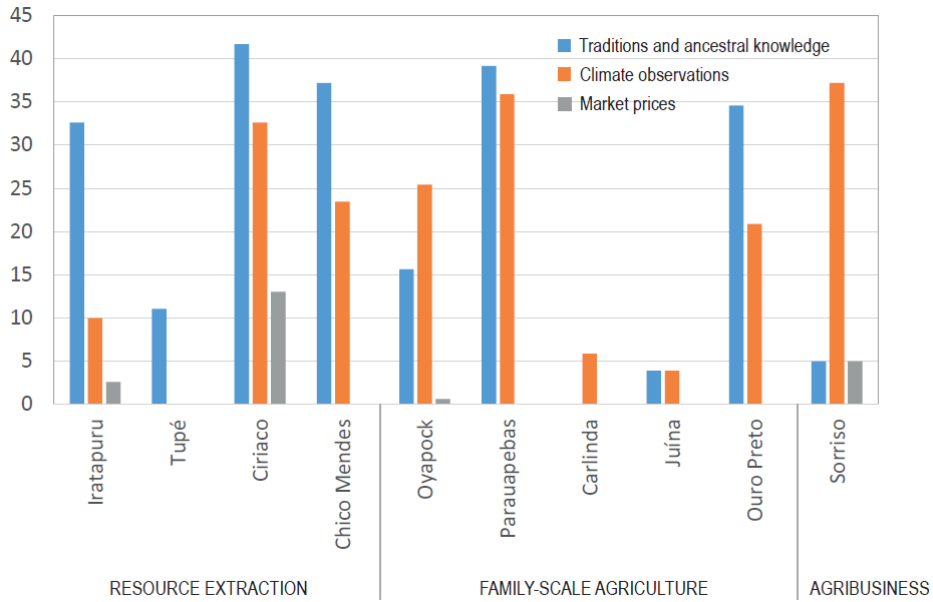
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**Fig. 6** Schematics of perceptions of rainfall changes in the 13 Amazonian study sites. The three first letters of each site are placed next to the symbols.

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**Fig. 7** Percentage of three types of responses given to the question “How do you plan your cultures?”