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1 Perceptions of climate and climate change by Amazonian 2 communities

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14
15 **Abstract** The Amazon region has been undergoing profound transformations since the late
16 '70s through forest degradation, land use changes and effects of global climate change. The
17 perception of such changes by local communities is important for risk analysis and
18 for subsequent societal decision making. In this study, we compare and contrast observations
19 and perceptions of climate change by selected Amazonian communities particularly vulnerable
20 to alterations in precipitation regimes. Two main points were analysed: (i) the notion of
21 changes in the annual climate cycle and (ii) the notion of changes in rainfall patterns. About
22 72% of the sampled population reports perceptions of climate changes, and there is a robust
23 signal of increased perception with age. Other possible predictive parameters such as gender,
24 fishing frequency and changes in/planning of economic activities do not appear overall as
25 contributing to perceptions. The communities' perceptions of the changes in 2013-2014 were
26 then compared to earlier results (2007-2008), providing an unprecedented cohort study of the
27 same sites. Results show that climate change perceptions and measured rainfall variations
28 differ across the basin. It was only in the southern part of the Amazon that both measured and
29 perceived changes in rainfall patterns were consistent with decreased precipitation. However,
30 the perception of a changing climate became more widespread and frequently mentioned,
31 signalling an increase in awareness of climate risk.

32
33 **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 km² 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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788

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790 characteristics of the DURAMAZ-2 study sites.

791

792 **Table 2** Univariate analysis of independent variables and perceptions (outcome variables).
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 σ 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 (τ)
812 was calculated to examine whether the percentage of report in climate change was influenced
813 by the irregular sample size, and σ 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 (τ)
820 was calculated to examine whether the % of report in climate change was influenced by the
821 irregular sample size; σ is the corresponding 2-sided significance.

822

823 **Table 7** Bivariate analysis: How do you predict the weather? vs perception reports. Values in
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 (τ) was calculated to examine whether the % of

827 report in climate change was influenced by the irregular sample size; σ is the corresponding 2-
828 sided significance.

829

830 **Table 8** Rainfall trends (mm/year; 1983-2012) and corresponding 95% confidence interval
831 based on PERSIANN-CDR estimates at the nearest grid point to the DURAMAZ-2 site. Perception
832 of rainfall changes at the Amazonian sites studied in the DURAMAZ-2 program. Each column
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; σ is the corresponding 2-sided significance.

837

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839

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

843

844 **Fig. 2** Synthetic chart of methodology process for obtaining first the independent variables
845 (directly connected to each level – sites, household, individual - , and the outcome variables used
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
854 PERSIANN-CDR for each DURAMAZ-2 site. Both quantities were counted from July to June the
855 following year. Lines correspond to the linear trend (1983-2012) for each parameter; trends are
856 not statistically significant.

857

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

860

861 **Fig. 6** Schematics of perceptions of rainfall changes by the 13 Amazonian study sites.

862

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)
		Hotter	96 (7.6)
Gender	1267	Drier	13 (1.0)
Male	673 (53.1)	Windier	11 (0.9)
Female	594 (46.9)	Weather extremes (drought,	
		flood)	37 (2.9)
		Temperature changes	4 (0.3)
Frequency of fishing	702		
Never	254 (36.2)	Reports changes in rainfall	
DK/DA	20 (2.9)	No	423 (33.3)
≤ 1x/year	29 (4.1)	Yes	848 (66.7)
1x/3mo	31 (4.4)	Intensity	354 (27.9)
1x/mo	72 (10.0)	Frequency	359 (28.3)
1x/15days	40 (5.7)	Unpredictability	245 (19.3)
1x/week	89 (12.7)		
≥ 2x/week	82 (11.7)	Suggests driver of climate change	
Irregularly	86 (12.3)	Didn't answer	557 (43.8)
Changes in activity in the		Don't know	185 (14.6)
last 3 years	702	Non-anthropogenic	187 (14.7)
No	100 (14.2)	Anthropogenic forcing	392 (30.8)
Seeding time	59 (8.4)	Deforestation	245 (19.3)
Abandoned a crop or		Dam building	65(5.1)
culture	88 (12.5)	Environmental/soil	
Started new culture(s)		degradation	33 (2.6)
.....	51 (7.3)	Other (cattle, fire, road, etc.)	49 (3.9)
Changes in livestock			
farming	7 (1)		
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 σ 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	88 (62.0)	74 (52.1)	12 (8.5)	58 (40.8)	37 (26.1)
21-25	129	81 (62.8)	75 (58.1)	14 (10.9)	58 (45.0)	36 (27.9)
26-30	127	86 (67.7)	77 (60.6)	15 (11.8)	59 (46.5)	35 (27.6)
31-35	149	110 (73.8)	98 (65.8)	13 (8.7)	82 (55.0)	42 (28.2)
36-40	130	94 (72.3)	88 (67.7)	15 (11.6)	68 (52.3)	36 (27.7)
41-45	112	80 (71.4)	72 (64.3)	12 (10.7)	58 (51.8)	27 (24.1)
46-50	104	82 (78.8)	69 (66.3)	16 (15.4)	54 (51.9)	31 (29.8)
51-55	107	87 (81.3)	80 (74.8)	23 (21.5)	56 (52.3)	26 (24.3)
56-60	92	77 (83.7)	72 (78.3)	11 (12.0)	49 (53.3)	25 (27.2)
61+	152	108 (71.1)	88 (57.9)	13 (8.6)	60 (39.5)	41 (27.0)
TOTAL	1244	893 (71.8)	793 (63.8)	144 (11.6)	602 (48.5)	336 (27.0)
r_s (σ)		0.70 (0.03)	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 (τ)
 894 was calculated to examine whether the percentage of report in climate change was influenced
 895 by the irregular sample size. and σ 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	185 (73.4)	157 (62.3)	51 (20.2)	197 (78.2)	65 (26.0)
DK/DA	19	15 (78.9)	10 (52.6)	1 (5.3)	18 (94.7)	6 (31.6)
≤ 1x/year	29	26 (89.7)	25 (86.2)	6 (20.7)	26 (89.7)	8 (26.7)
1x/3mo	31	19 (61.3)	18 (58.1)	5 (16.1)	14 (45.2)	7 (21.9)
1x/mo	71	55 (77.5)	49 (69.0)	8 (11.3)	70 (98.6)	29 (41.4)
1x/15days	39	31 (79.5)	30 (76.9)	7 (18.0)	38 (97.4)	14 (35.9)
1x/week	87	66 (75.9)	62 (71.3)	13 (14.9)	71 (81.6)	27 (31.0)
≥ 2x/week	81	52 (64.2)	48 (59.3)	8 (9.9)	51 (63.0)	15 (18.5)
Irregularly	86	65 (75.6)	59 (68.6)	15 (17.4)	78 (90.7)	25 (28.7)
TOTAL	695	514 (74.0)	458 (65.9)	114 (16.4)	563 (81.0)	196 (28.2)
r_s (σ)		-0.1 (0.8)	-0.1 (0.9)	-0.8 (0.04)	0 (1.0)	0 (1.0)
τ (σ)		-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 (τ)
 903 was calculated to examine whether the % of report in climate change was influenced by the
 904 irregular sample size; σ 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	63 (74.1)	61 (71.8)	26 (30.6)	80 (94.1)	27 (31.4)
Seeding time	51	45 (88.2)	40 (78.4)	7 (13.7)	44 (86.3)	16 (31.4)
Abandoned crop/culture	82	62 (75.6)	55 (67.1)	17 (20.7)	61 (74.4)	35 (42.2)
Started new culture	43	26 (60.5)	24 (55.8)	8 (18.6)	29 (67.4)	18 (41.9)
Livestock	6	3 (50.0)	3 (50.0)	3 (50.0)	1 (16.7)	1 (16.7)
Other	66	52 (78.8)	51 (30.3)	20 (30.3)	55 (83.3)	30 (46.2)
DK/DA	296	224 (75.7)	185 (83.3)	29 (9.8)	227 (76.7)	55 (18.6)
TOTAL	629	475 (75.5)	419 (66.6)	110 (17.5)	497 (78.9)	182 (28.9)
τ (σ)		0.2 (0.5)	0.1 (0.7)	-0.2 (0.5)	0.4 (0.2)	0.1 (0.9)

906

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 (τ) was calculated to examine whether the % of
 912 report in climate change was influenced by the irregular sample size; σ 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	279 (69.6)	239 (59.6)	80 (20.0)	305 (76.1)	104 (25.9)
Does not use TV/radio/etc	40	28 (70.0)	26 (65.0)	11 (27.5)	31 (77.5)	9 (22.5)
Life exper.	42	34 (81.0)	29 (69.0)	2 (4.8)	23 (54.8)	15 (35.7)
Comb.of the two above	151	124 (82.1)	115 (76.2)	21 (13.9)	123 (81.5)	48 (31.8)
	19	17 (89.5)	17 (89.5)	0 (0)	15 (78.9)	8 (42.1)
TOTAL	653	482 (73.8)	426 (65.2)	114 (17.5)	497 (76.1)	184 (28.2)
τ (σ)		-0.4 (0.3)	-0.4 (0.3)	0.4 (0.3)	-0.2 (0.6)	-0.4 (0.3)

915

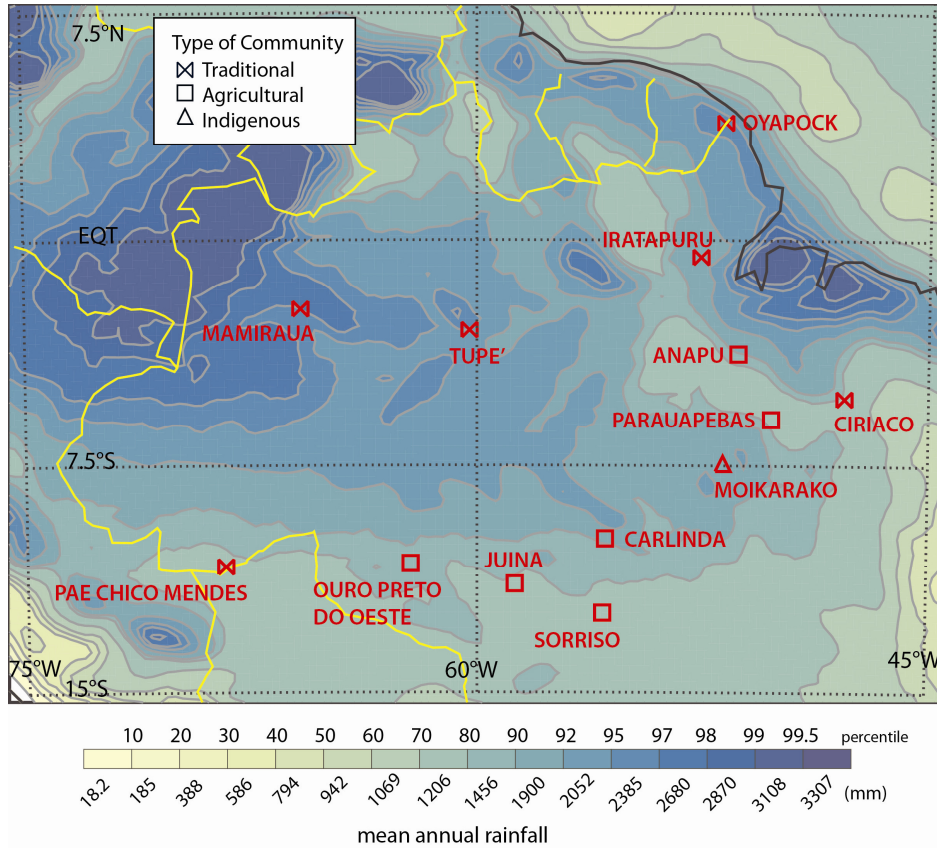
916

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; σ is the
 924 corresponding 2-sided significance.

925

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 (σ)		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)

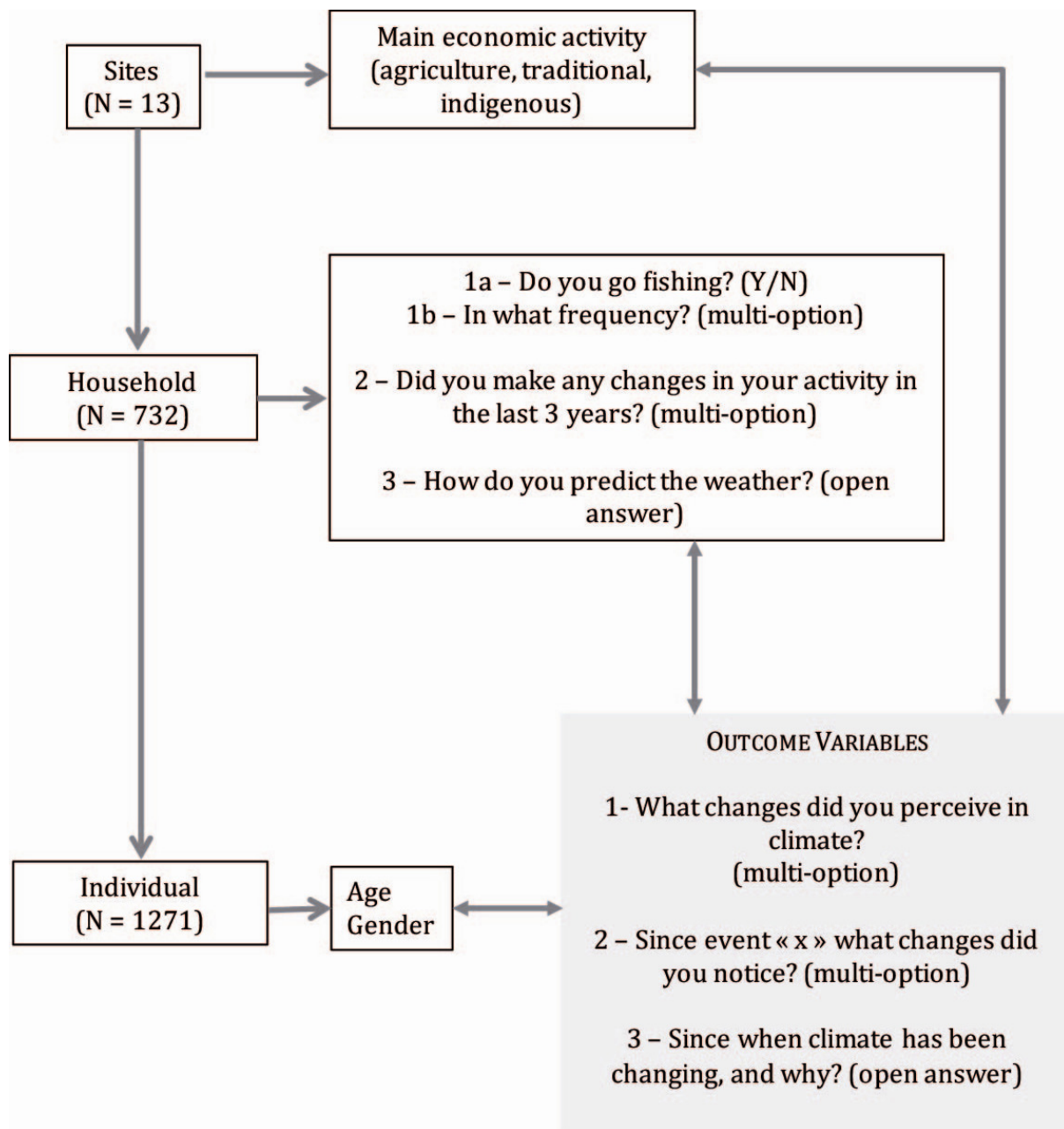
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Fig. 1 PERSIANN-CDR based mean annual rainfall (1983-2012) in the Amazon region. Red symbols show the study sites. The year 1992 was not included as data for February is not available.

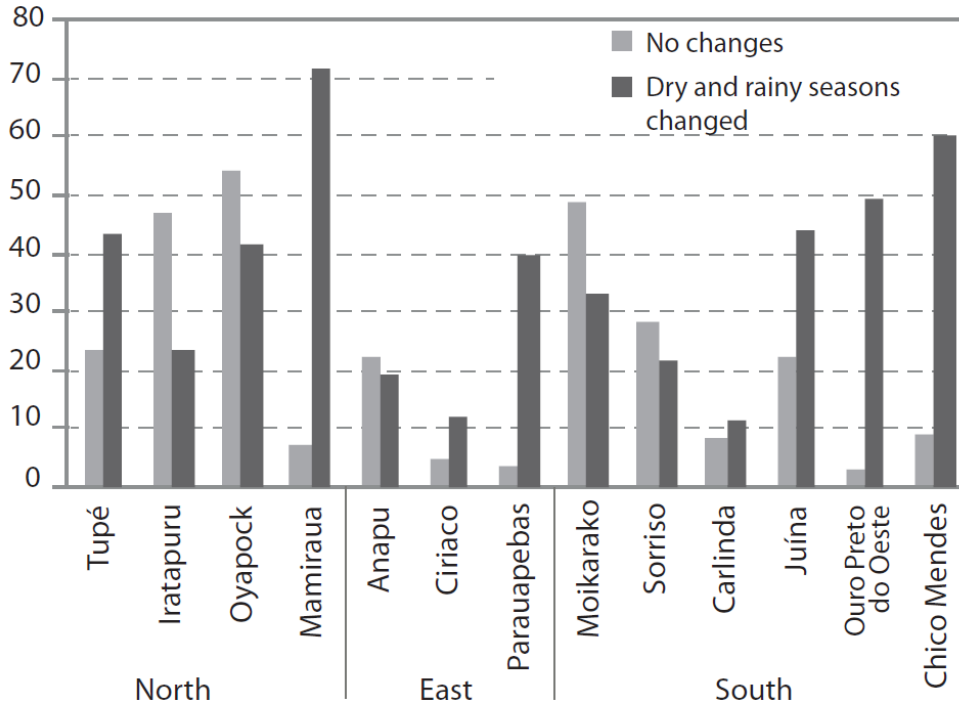
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Fig. 2 Schematics of methodology process for obtaining first the independent variables (directly connected to each level – sites, household, individual - , and the outcome variables used in this study. “Multi-option” answers denote closed-type questions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

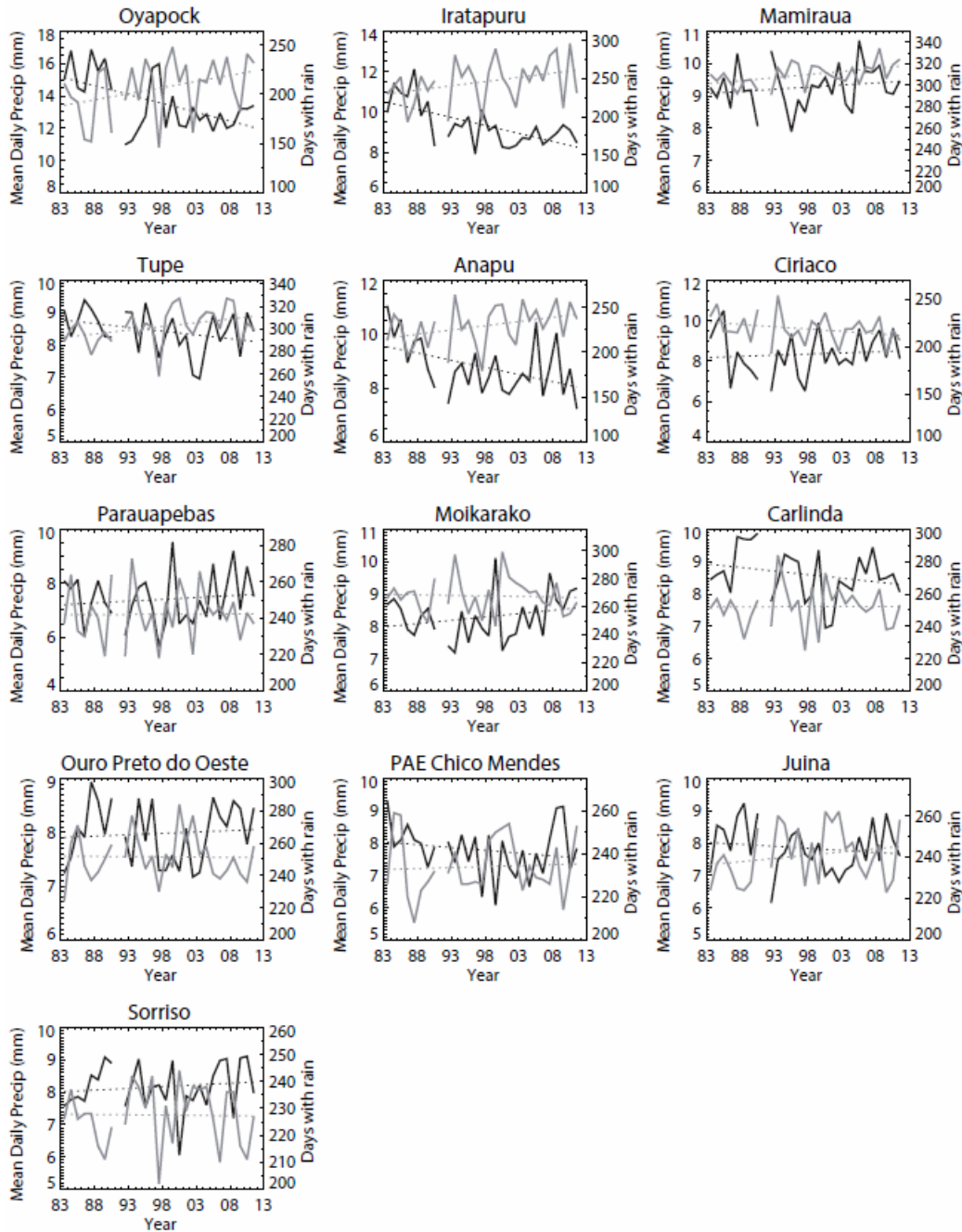
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Fig. 3 Percentage of population at each site that observed changes both in the dry and rainy seasons, or that did not observe any changes.

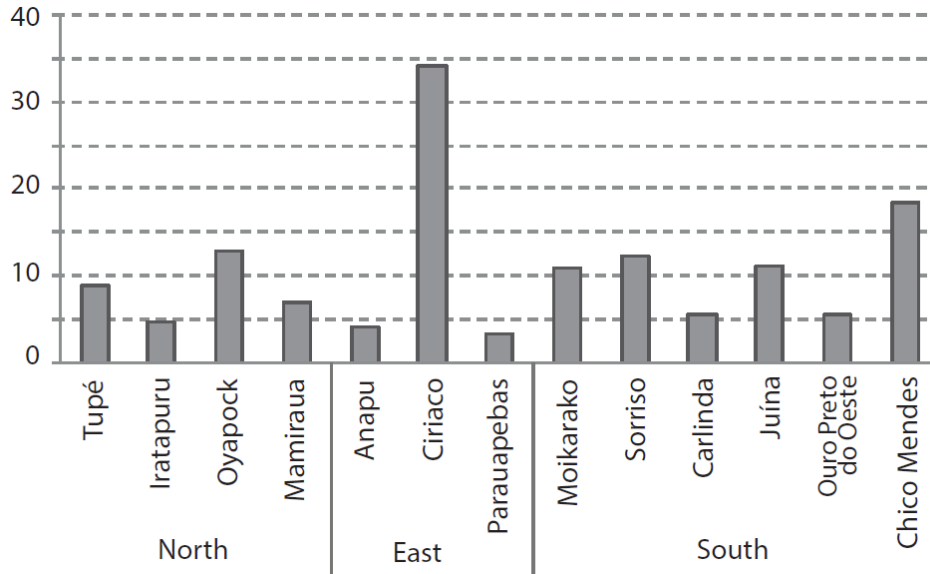
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Fig. 4 Mean daily rainfall (black), and total number of days with rain (gray), based on PERSIANN-CDR for each DURAMAZ-2 site. Both quantities were counted from July to June the following year. Lines correspond to the linear trend (1983-2012) for each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

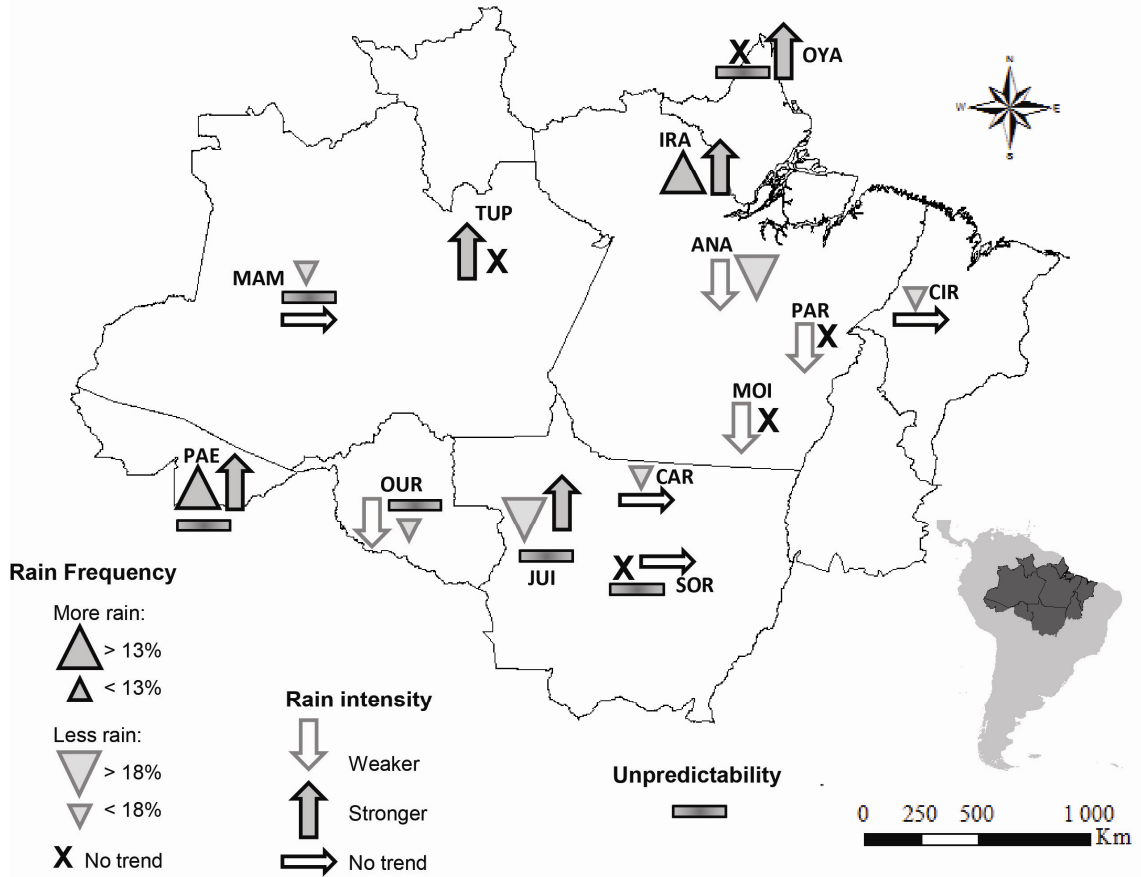
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Fig. 5 Percentage of answers concerning the perception of displacement of rainy season, per site.

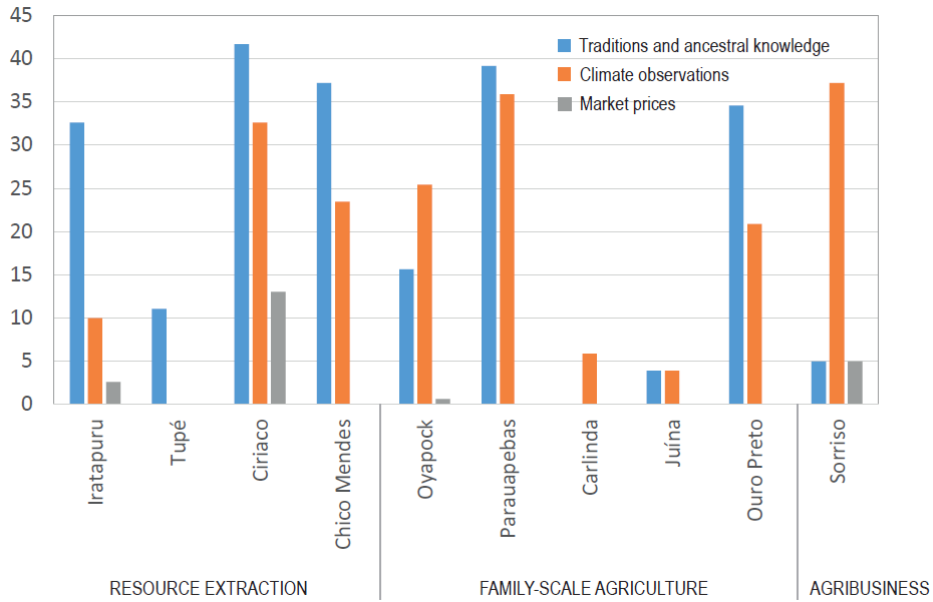
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Fig. 6 Schematics of perceptions of rainfall changes in the 13 Amazonian study sites. The three first letters of each site are placed next to the symbols.

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