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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.

1. Introduction

1.1. Climate change debate and perceptions

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

The study of perceptions is important as a support for risk analysis and for preparing public response to hazards. It can also help in communicating risk information among the local population, the technical experts and the policy makers (Noble et al., 2014; Sterman, 2008; Farjam et al., 2018). Rudiak-Gould (2014) showed that climate science communication has a significant impact on climate perceptions: climate science awareness was a better predictor of environmental change perceptions than exposure to the environment. If we start with the hypothesis that mitigation of (and/or adaptation to) climate change is linked to first-hand experience of its potential consequences (for example, higher frequency and intensity of droughts, floods, heat waves or cold spells, etc.), then it follows that individuals who have had these

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experiences may be more inclined to adopt sustainable behaviours and/or adaptation practices (Spence et al., 2011a, 2011b, and references therein). This hypothesis has been tested in the US and the UK with mixed results. Spence et al. (2011a, 2011b) and Rudiak-Gould (2014) found that people affected by floods became more responsive and sensitive to energy and climate change issues, while Coles and Scott (2009) found that, due to economic constraints (cost of adaptation), traditional knowledge is favoured instead of seasonal climate predictions in defining agricultural and ranching practices. Understanding the underlying drivers that encourage local people to adapt to climate change helps with forging programs and strategies that can have a better chance for a positive outcome (Slovic et al., 1982; Leiserowitz, 2006; Weber, 2006, 2010; Howe et al., 2013; Neethling et al., 2016; Spence et al., 2011a, 2011b, Noble et al., 2014; Garret et al., 2017; Bakaki and Bernauer, 2017).

1.2. Climate change observations in the Amazon region

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

Several climate studies based on observations and numerical model simulations of the climate in the Amazon have pointed to an increase in temperature, as well as a decrease in the duration of the rainy season and a strengthening of the water cycle and runoff (e.g., Oyama and Nobre, 2003; Fu et al., 2013; Debortoli et al., 2015; Gloor et al., 2013; Swann et al., 2015; Guimberteau et al., 2017; Arvor et al., 2017b; Nobre et al., 2016). The combined effect of large-scale climate change and local deforestation is more difficult to assess. For example, the impact of the Amazon fragmentation on climate is not well understood, and land cover subsequent to deforestation is an important factor on the degree of projected climate change (Sampaio et al., 2007; Correia et al., 2008; Malhi et al., 2008; Lawrence and Vandecar, 2015). A range of climate model studies showed a trend toward forests being replaced by lower vegetation (savanna or seasonal forests) in the southern part of the Amazon that was caused by a combination of the effects of increased temperature and a longer dry season, this forecasted in most models by 2100 (Cook et al., 2012). In addition, years with more intense floods (such as those of 2009 and 2014) could increase forest resilience by providing a surplus of residual soil moisture that would be available for the following year. Thus, there are various forcings and uncertainties in the climate projections. These uncertainties propagate through temporal and spatial scales, but there is evidence that, mainly in its southern and eastern parts, the Amazon basin ecosystem is transitioning to a disturbed regime with changes in the energy and water cycles (Davidson et al., 2012). At a regional scale such as the Amazon, it is necessary to consider several nested spatial scales to address the impact of climate change on ecosystems. Deforestation, agricultural practices, road construction and other activities contribute to the degradation of the forest ecosystem and resources and influence local and regional climate, the economy and public health (Davidson et al., 2012; Brondízio et al., 2016; Nobre et al., 2016).

1.3. Reconciling climate change observations and perceptions in the Amazon region

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

A study on how traditional knowledge and meteorological data influence family-scale farming has demonstrated that local farmers in the semi-arid Northeast of Brazil do not change their practices, mostly because of the lack of both technical and cultural alternative solutions (Nasuti et al., 2013). In the latter case, all actions - or reactions - to perceived changes were aimed at short-term solutions, not long-term plans for adaptation.

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

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

2. Data and methods

2.1. Study sites and questionnaires

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

Fig. 2 shows a synthetic chart depicting the methodology process used to gather data on both independent and outcome (perception) variables. The methodology employed sought an optimal social-demographic sampling of the population (Dubreuil et al., 2017; Le Tourneau et al., 2013) and used a scale refinement at each stage. First, general information on institutional and geographical aspects were collected at site scale. Socio-economic data were then collected at the household

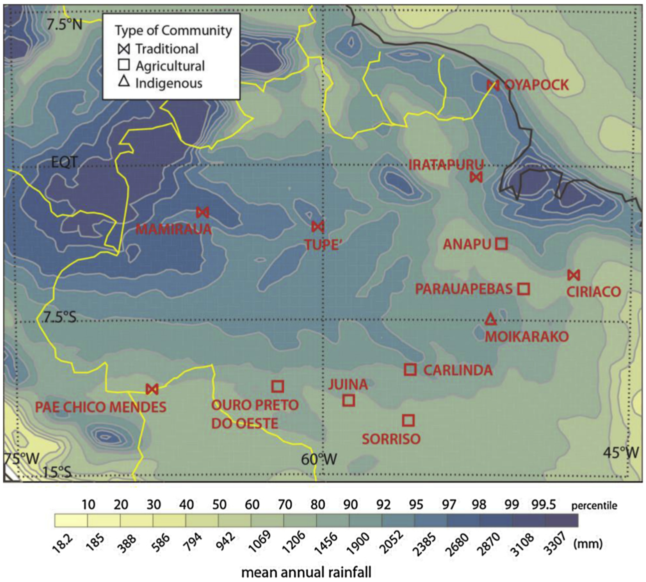

Fig. 1. PERSIANN-CDR based mean annual rainfall (1983–2012) in the Amazon region. Red symbols show the study sites. The year 1992 was not included as data for February is not available (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article).

level by means of a specific questionnaire, and further completed by another questionnaire at the individual level. The sampling rules were to interview all households for sites with fewer than 75 houses or conduct a representative sampling of the population in sites that had more than 75 houses. For each house included in the sample, interviews based on the individual questionnaire were conducted with the head of household and his/her spouse, as well as with any children aged 15 or older. Thus, individual questionnaires could explore differences in behaviour and in perceptions across several age groups. In total, 747 households were visited, 1271 individuals were interviewed, and information was recorded on 2258 people.

The analysis of perceptions of climate in the current study was inspired by the work performed by the Brazilian Network on Global Climate Change Research ("Rede CLIMA"; Arraut et al., 2012; Lindoso et al., 2014). The communities' economy, such as crops, livestock and extractivism, strongly depends on natural resources. The close relationship between these and the climate - in particular precipitation - makes these communities vulnerable to projected and/or ongoing climate changes (Arraut et al., 2012; Nobre et al., 2016). The central and southern parts of the Amazon which are under the influence of the South American Monsoon System (Marengo et al., 2012; Vera et al., 2006) present well-defined rainy and dry seasons, roughly an austral summer and winter respectively. In the northern part, rain is present most of the year, with seasonality represented by periods of more or less precipitation. Due to the importance of rainfall variations (especially for the communities that depend largely on water availability), the

Table 2
Univariate analysis of independent variables and perceptions (outcome variables). "DK/DA" denotes "don't know/didn't answer".

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

Table 1
Name (locality and state), geographical coordinates (shown in Fig. 1), and basic characteristics of the DURAMAZ-2 study sites.

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

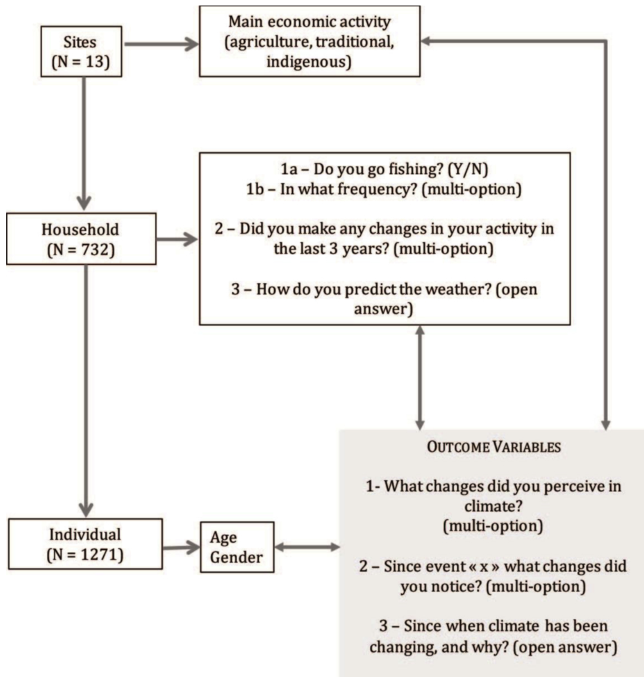

Fig. 2. Synthetic chart of methodology process for obtaining first the independent variables (directly connected to each level – sites, household, individual -, and the outcome variables used in this study. “Multi-option” answers denote closed-type questions (unless the option “Other, elaborate” was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

analysis of perceptions was organized around two main criteria: (i) perception of changes during the rainy/dry seasons (annual climate cycle), and (ii) perception of changes in rainfall patterns.

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

As a first step, univariate analysis was performed to obtain a general overview of the sample population and perceptions. A bivariate analysis was then performed to cross-evaluate the relationship between independent variables and perceptions. Notice that the liaison between sites, households and individuals was made through household indexing per site. For each household only one individual answer was considered, that of the household head who was usually the eldest member of the family.

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

2.2. Rainfall data: sources and linear trends

In this study, we analysed trends in annual rainfall totals and also mean daily rainfall and the number of days with rain. The latter two parameters were used as proxies for intensity and frequency of rain. The main set of rainfall data consists in the PERSIANN-CDR (”Precipitation by Remote Sensing Information using Artificial Neural Networks - Climatic Data Record”) satellite-derived precipitation estimates (Ashouri et al., 2015; Sorooshian et al., 2014). Satellite-based rainfall estimates are essential over the Amazon region as ground measurements are heterogeneous in time and space and often of dubious quality (Debortoli et al., 2015; Delahaye et al., 2015; Ronchail et al., 2002). Precipitation estimates by satellites are the only data available for localities where conventional ground-based measurements are non-existent. The PERSIANN-CDR dataset, available for the period 1983-delayed present, was recently released by the National Oceanic and Atmospheric Administration (NOAA). It provides daily precipitation estimates at a spatial resolution of 0.25° latitude by 0.25° longitude (~28 km). Data from the 1983–2012 period was used except for the year 1992 which was excluded as there was no data available for February. Dubreuil et al. (2017) and Arvor et al. (2017b) showed that PERSIANN-CDR estimates can realistically capture spatial and seasonal precipitation features and differences across the basin, with spatial resolution good enough to represent the “community” scale. For this study, we estimated the long-term trends (1983–2012) of annual totals and the number of days with rain using simple linear regression, and we used the methodology of Hauchecorne et al. (1991) (see also Santer et al., 2000) to measure the confidence interval of the estimated trend. The confidence interval depends on both the variance of the random component - which includes the short-term variability of the atmosphere and the measurement noise - and the correlation between two successive measurements. We provided the 2-sigma range (equivalent to 95% significance), commonly used to define the confidence interval. In the Amazon region, trends in precipitation are typically smaller than its confidence interval, indicating that natural variability of the system dominates the variability signal (e.g., Davidson et al., 2012).

3. Results

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

3.1. Univariate analysis

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

Table 2 shows that the sampling was fairly equitable regarding gender (53.1% men, 46.7% women) and even regarding age, with slightly more population under 40 (54.4%) than above. This proportion is close to that of the total population in rural Amazonia, which is approximately 60/40 for below/above 40 year-olds (removing those below 15; https://sidra.ibge.gov.br/home/pms/brasil). The other independent variables chosen (frequency of fishing, changes in activity, and weather forecasting) indicate a rather heterogeneous distribution.

The outcome variables reveal an overwhelming perception of climate change in general (~72%) and of rainfall changes (~65%). Other elements of climate (winds, temperature and humidity) were also brought up spontaneously (12.7%), with increased temperature being often mentioned (11.3% of total answers). This can be partially attributed to influence from media outlets that report impacts of global warming, but it also corresponds to the (rare) temperature observations in the Amazon (e.g., Victoria et al., 1998).

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

3.2. Bivariate analysis

Tables 3–7 show the results of a bivariate analysis. Results were tested for significance against a binomial distribution (2-tailed test), with the null hypothesis being a random chance of getting a yes/no answer to each perception question. All tests were performed using the raw counts for each class. Results were further tested against bias in the sampling size by means of non-parametric, ranking correlation. These correlations showed that the estimated percentage values were unaffected by the sampling size, except for the "weather prediction" parameter.

The results show that there is a significant increase of climate change reports with age (r_s = 0.7; Table 4), congruent with the notion of "shifted time baseline". As stated by Hansen et al. (2012), "a perceptive person old enough to remember the climate of 1951–1980 should recognize the existence of climate change", however those exposed to a more recent climate baseline (e.g., 1981–2010) would not have the same perception "as they include the years of rapidly changing climate within the base period, making it more difficult to discern the changes that are taking place".

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

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

3.3. Rainfall trends and perceptions in the Brazilian Amazon

Many previous studies have pointed to changes in rainfall across the Amazon (Almeida et al., 2016; Arvor et al., 2017b; Debortoli et al., 2015; Espinoza Villar et al., 2009). Rainfall trends may be more or less

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

	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)

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

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

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

	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)

significant depending on the season and the geographical location, but in general these studies have pointed towards a shortening of the rainy season, frequently associated to weaker intensity of precipitation at the beginning of the season (Debortoli et al., 2015; Dubreuil et al., 2012). We re-examined the reports of rainfall changes (compiled for all sites in Table 2), including spatial perspective. For example, Fig. 3 shows that perceptions of rainy/dry season changes (question (i)) are clearly heterogeneous across sites: six sites (Chico Mendes, Oyapock, Parauapebas, Ouro Preto do Oeste, Mamiraua, Juína and Tupé) presented a 40% or higher rate of changes in both rainy and dry seasons. To a lesser degree, this response was seen in populations in Moikarako, Sorriso and Iratapuru (33%, 21% and 24% respectively). In the latter sites, the strongest response was that changes in climate have been neither observed nor felt (49%, 29%, and 43%, respectively). Finally, only two sites reported a higher rate of perception of changes in the rainy season only, namely Ciriaco (37%) and to a lesser degree Carlinda.

Next, we focused on the observed rainfall trends at each of the 13 sites. Table 8 shows linear trends based on PERSIANN-CDR data, along

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

	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	40	**28 (70.0)**	26 (65.0)	**11 (27.5)**	**31 (77.5)**	**9 (22.5)**
TV/radio/etc	42	**34 (81.0)**	**29 (69.0)**	**2 (4.8)**	23 (54.8)	15 (35.7)
Life exper.	151	**124 (82.1)**	**115 (76.2)**	**21 (13.9)**	**123 (81.5)**	**48 (31.8)**
Comb.of the two above	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)

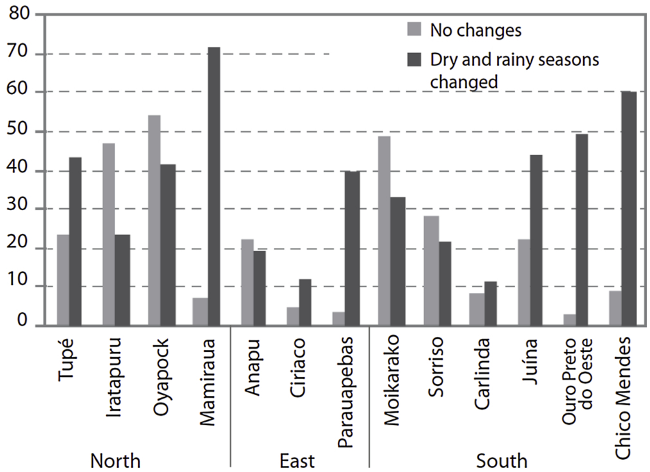

Fig. 3. Percentage of population for each study site that observed changes both in the dry and rainy seasons, or that did not observe any changes.

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

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

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

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

How well do these perceptions correspond to those estimated by physical measurements? We found no significant correlation between rainfall trends and any perception (Table 8), nor between the magnitude or amplitude of interannual variability and perceptions of rainfall changes (not shown). This result is in line with the bivariate analysis previously shown which suggested no link between personal sensibility or exposure to the environment and perceptions of climate change. Nevertheless, an analysis of satellite-based estimates and perceptions shows that, although there is no linear relationship between changes in rainfall amounts and perceptions, they are qualitatively congruent in most of the study sites with respect to trends in intensity of rainfall (Figs. 2 and 6). Six sites present similar trends between observed and perceived data: increasing intensity at Iratapuru, Chico Mendes, decreasing at Ouro Preto do Oeste and no changes at Parauapebas, Moikarako and Sorriso. Only at Juína were the results somewhat disparate, with positive rainfall intensity trends detected by PERSIANN-CDR, but lower frequency revealed by the interviews; this is also the only site where the respondents answered that the rain frequency decreased but with increased intensity.

An approximate three-zone spatial arrangement can be discerned (Fig. 6):

– The communities of Oyapock, Iratapuru, Tupé and PAE Chico

Table 8

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

DUR-2 Site	Linear Trends (mm/yr)	Increased rainfall intensity	Decreased rainfall intensity	Rainy season displace-ment	Unpredict-ability	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)

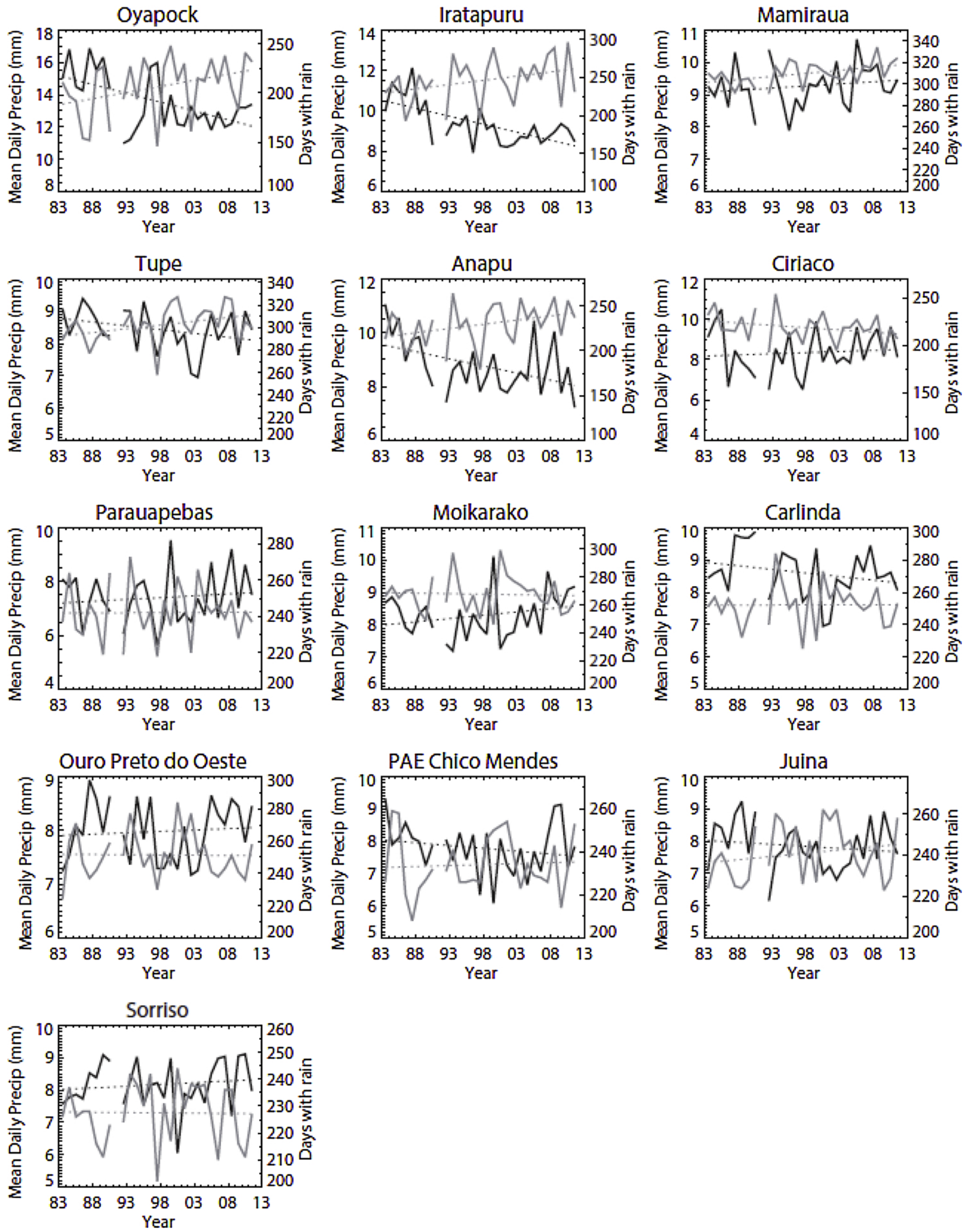

Fig. 4. Mean daily rainfall (black), and total number of days with rain (gray), based on PERSIANN-CDR for each DURAMAZ-2 site. Both quantities were counted from July to June the following year. Lines correspond to the linear trend (1983–2012) for each parameter; trends are not statistically significant.

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

Mendes (in the north and western parts of the domain) present notions of increasing trends in precipitation, in volume or intensity, or both. These perceptions do not match trends based on rainfall observations. In Mamiraua, no trends in rainfall frequency or intensity were perceived, while a slight increase in rain frequency has been detected.

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

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

Finally, the unpredictability of rainfall is mentioned by nearly all interviewees, albeit in different degrees. Oyapock and Mamiraua are the sites in which this aspect was the most strongly mentioned (37.0 and 31.6%, respectively), followed by Ouro Preto do Oeste (22.8%) and PAE Chico Mendes (24.5%). Fig. 6 indicates that the unpredictability

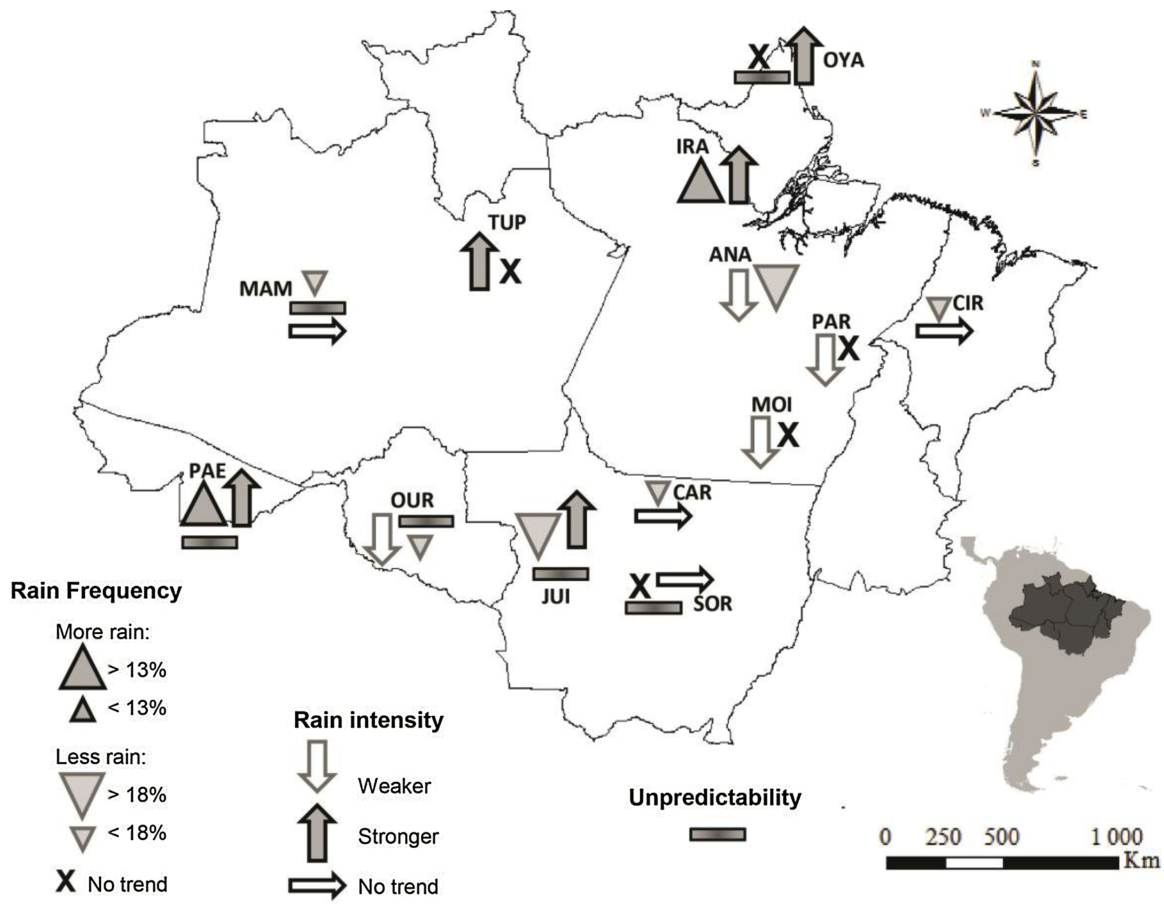

Fig. 6. Schematics of perceptions of rainfall changes by the 13 Amazonian study sites.

aspect does not present a spatial coherence or preference, nor does it coincide with frequency or intensity of rainfall.

3.4. Temporal changes in perceptions

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

All sites indicated most frequently a warmer climate, consistent with previous responses to questionnaires undertaken 5 years earlier. The most striking element in "open answers" back in the first data collection was the increase of the irregularity (or unpredictability) of rainfall. This perception is still a salient result in the DURAMAZ-2 project. Both agricultural-based and traditional communities (that is

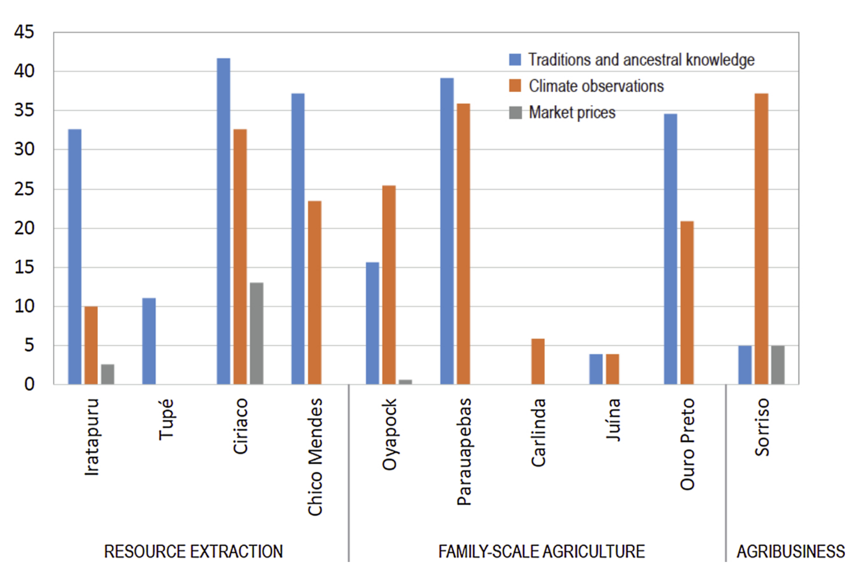

Fig. 7. Percentage of three types of responses given to the question "How do you plan your cultures?".

those that count on fishing, extractivism, and/or family-scale agriculture) seem primarily sensitive to the interannual variability of rainfall. The arc of deforestation in the southern Brazilian Amazon clearly shows a concurrence of lower rainfall and higher perception of rainfall change by communities. This feature persisted into the second phase of the DURAMAZ project and is particularly noteworthy as the 2013–2014 rainy season was locally wetter than in 2008-2009. The most relevant difference with respect to the earlier finding was that comments on global warming were spontaneously brought up among the interviewees (included in response "Others"), indicating a heightened climate change awareness.

3.5. Connections between agricultural practices and climate observations and perceptions

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

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

Changes in recent practices or types of production related to climatic changes were reported only in the Mato Grosso state (38.9% of total answers) and correspond to a better adaptation to environmental conditions. For example, several producers in Juína began to irrigate their plots to secure the production and make it effective throughout the year. In Carlinda, conversion from agriculture to dairy production led livestock farmers to try to cushion the decline in production (and hence the loss of income) during the dry season by developing water reservoirs or by supplementing fodder crops from May to September. In Sorriso, there was a general replacement of single seeding to the dual-cropping ("safra-safrinha") system aiming at extending land productivity throughout the rainy season (Arvor et al., 2014). Lastly, there was an increase in the practice of irrigation at the beginning of the dry season for certain crops (e.g., beans; Arvor et al., 2018). These examples attest to efforts to adapt farming practices according to perceived changes in climate. The main motivation though is economic rather than for environmental awareness reasons.

4. Discussion and final remarks

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

As scientists aim at quantifying climate change – arguably to render it "visible" (e.g., Rudiak-Gould, 2013) - people at the frontline of deforestation and land cover changes in the Amazon region have their own perceptions of change. Generally, comparing physical quantities with social data on perceptions is delicate, as it may lead to a hierarchical reading between "the true nature" whose study is an attribute of natural scientists, and the "culturally constructed" nature, whose study is an attribute of social scientists (Brondízio and Moran, 2008; Ingold, 2000; Morton, 2007; Swim et al., 2009; Rudiak-Gould, 2013). However, introducing a "subjective" dimension in vulnerability analysis is important: the metrics of the natural sciences are fundamental to define, calculate and predict climate change, but are not sufficient to establish strategies on how to address the problems, especially at the local level. As such, we aimed at comparing and contrasting independent, measured data against perceptions and examined possible links that could explain a given notion of change.

About 72% of the sampled population (N = 1271) perceived changes in climate. A statistically robust increase in perception of change with age was found, congruent with the "shifted baseline" concept (Hansen et al., 2012). This increased perception with age was also found by e.g., Rudiak-Gould (2014) and Alessa et al. (2008) who studied indigenous and native communities in the Marshall Islands and in the Seward Peninsula (Alaska), respectively. On the other hand, climate change perception studies for New Zealand and for European countries have shown that older age groups, particularly those with fewer years of formal education, tend to acknowledge to a lesser degree the existence and anthropogenic nature of climate change (Poortinga et al., 2011, 2019; Milfont et al., 2015). Moreover, in these latter areas, men were more likely to doubt climate change than women, whereas in rural Amazonia gender did not appear as a significant factor to explain reports of climate change (also reported by Alessa et al., 2008).

Other factors such as environmental exposure (fishing) and personal experience (change in activity, agricultural planning, weather forecasting) also did not appear to affect perception reports. A similar finding was documented by Rudiak-Gould (2014). However, studies conducted with communities in the Arctic region indicate increased climate change perceptions with environmental exposure and with the transmission of traditional knowledge by the elders (e.g., Riedlinger and Berkes, 2001; Furgal and Seguin, 2006; Alessa et al., 2008; Wolf and Moser, 2011). In the Arctic region, the notion of "visibility" of climate change takes full meaning as the Artic is a hot spot of vulnerability to climate change (Giorgi, 2006) and environmental changes can be more "visible" – for example the sensible reduction in the seasonal extent and distribution of sea ice, wildlife abundance and health, permafrost thaw – compared to changes in the tropical regions.

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

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

This study went beyond still by looking at the connections between agricultural practices and climate calendar. Economic activities with links to rainfall are sensitive to its interannual variability and extreme events. However, for some sites, crop planning is linked to market prices and thus can evolve dynamically to remain competitive in the market. The production of the most lucrative products is favoured, particularly at the Sorriso and Ciriaco sites. Adaptation to climate variations is more frequently observed within the agricultural communities in the south (e.g., Sorriso and Juína): in order to adapt to the constraints of rainfall fluctuations, irrigation has become more frequent in the Amazon. Artificial ponds, created on river networks to ensure water supply for maize and cotton crops, have multiplied across the southeastern agricultural frontier (Arvor et al., 2018), raising questions on the potential negative effects on hydrology, biodiversity, geochemistry of soils and global warming across temporal and spatial scales. Other adaptive measures, seen at Juína, include the abandon of a crop, change of crop, alterations in the seeding date and implementation of greenhouses.

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

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