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Does the Future Affect the Present? The Effects of Future Weather on the Current Collection of Planted Crops and Wildlife in a Native Amazonian Society of Bolivia

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Abstract Unlike neighboring disciplines, anthropology rarely studies how actual future events affect current behavior. Such studies could lay the groundwork for studies of ethnoforecasting. Psychologists argue that people forecast poorly, but some empirical work in cultural anthropology suggests that at least with weather, rural people might make reasonably accurate forecasts. Using data from a small-scale, pre-industrial rural society in the Bolivian Amazon, this study estimates the effects of future weather on the current collection of planted crops and wildlife. If actual future events affect current behavior, then this would suggest that people must forecast accurately. Longitudinal data covering 11 consecutive months (10/2002–8/2003, inclusive) from 311 women and 326 men ≥age 14 in 13 villages of a contemporary society of forager-farmers in Bolivia's Amazon (Tsimane') are used. Individual fixed-effect panel linear regressions are used to estimate the effect of future weather (mean hourly temperature and total daily rain) over the next 1–7 days from today on the probability of collecting wildlife (game, fish, and feral plants excluding firewood) and planted farm crops (annuals and perennials) today. Daily weather records come from a town next to the Tsimane' territory and data on foraging and farming come from scans (behavioral spot observations) and surveys of study participants done during scans. Short-term future weather (≤3 days) affected the probability of collecting planted crops and wildlife today, although the effect was greater on the amount of planted crops harvested today than on the amount of wildlife

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collected today. Future weather beyond 3 days bore no significant association with the amount of planted crops harvested today nor with the amount of wildlife collected today. After controlling for future and past weather, today's weather (mean hourly temperature, but not rain) affected the probability of collecting wildlife today, but today's weather (temperature or rain) did not affect the probability of collecting planted crops today. The study supports prior work by anthropologists suggesting that rural people forecast accurately. If future weather affects the probability of harvesting planted crops and collecting wildlife today, then this suggests that Tsimane' must forecast accurately. We discuss possible reasons for the finding. The study also supports growing evidence from rural areas of low-income nations that rural people tend to protect their food production and food consumption well against small idiosyncratic shocks or, in our case, against ordinary daily weather that is not extreme. However, the greater responsiveness of daily foraging output compared with daily farming output to today's weather suggests that foraging might not protect food consumption as well as farming against adverse climate perturbations.

Keywords Weather · Weather forecasts · Amazon · Bolivia · Tsimane' · Foragers · Hunter gatherers · Vulnerability · Forecasting

Introduction

In this article we address a simple question that has received scant attention from anthropologists: Do actual events in the future determine current behavior after conditioning for the role of past and current confounders? To do so we use an unusual data set: longitudinal data collected over 11 consecutive months (October 2002–August 2003, inclusive) from a low-income, contemporary foraging and farming society of native Amazonians in Bolivia (Tsimane'). The data set contains information on daily weather (temperature and rain), behavioral spot observations (or scans) of study participants, and survey data on daily amounts of planted farm crops and wildlife collected. We use the data to estimate the effect of future weather (mean hourly temperature and total daily rain) over the next 1–7 days on the probability of collecting wildlife (game, fish, and feral plants excluding firewood) and planted farm crops (annuals and perennials; hereafter *planted crops*) today. To enhance the likelihood that our estimates in fact capture the effect of future weather on today's behavior, we control for the confounding role of the following: (1) the weather today, (2) the weather during the previous 7 days, and (3) variables such as age, sex, schooling, and the date and the time we observed behavior.

As well as filling a gap in the empirical work of anthropology, this question has theoretical significance. First, the analysis of how actual future events shape present behavior could provide the empirical and intellectual rationale for studies of ethno-forecasting. To show that actual future events influence present behavior would lay the empirical groundwork for assessing how people form expectations and forecast (Tucker 2007).

Second, empirical work by psychologists about the accuracy of forecasts and ethnographic work by anthropologists about subsistence decisions provide conflicting hypotheses about what to expect when estimating the effect of future events on current behavior. Psychologists have amassed considerable evidence from industrial nations to suggest that ordinary people and experts make inaccurate predictions about a wide range of future events because they selectively see and pick out patterns in the past that do not in fact exist and use those patterns to predict the future, or because they focus on too narrow a range of predictors and ignore how other events might affect the forecast (Kahneman and Tversky 1973; Nisbett and Ross 1980; Vallone *et al*. 1990; Schkade and Kahneman 1998; Dunn *et al*. 2007; Finkenauer *et al*. 2007; Aamodt and Wang 2008). In particular, people are poor at judging contingency and accurately estimating covariation. Tucker (2007) found that the Mikea of Madagascar have a common, culturally shared understanding that rainfall is positively associated with the harvest of some crops and negatively associated with the harvest of other crops, but at the individual level they failed to successfully apply this simple and accurate heuristic because of memory lapses. Even political analysts whose reputation depends on the accuracy of their political forecasts provide no more accurate forecasts of political events than the lay public (Tetlock 2005). Research also suggests that the ability to predict accurately might vary across cultures (Ji *et al*. 2001; Lam *et al*. 2005; Sprott *et al*. 2006; Knuff 2007). If this is correct, it would suggest that actual future events should have a negligible effect on current behavior because people predict inaccurately most of the time.

However, research by cultural anthropologists (Orlove *et al*. 2000; Roncoli *et al*. 2002; Strauss and Orlove 2003; Moran *et al*. 2006) suggests that rural people who depend on rural-based activities for their subsistence make reasonably accurate predictions of the weather. If this is correct it would suggest that weather in the future (particularly in the short and medium term) should affect current behavior.

The empirical work we present here is designed to help test these two competing approaches, but from a novel angle. Rather than compare forecasts with the actual future event, we assess whether the actual future event in fact influences present behavior. If it does, then one can reasonably infer that people must be forecasting accurately, though it leaves open the mechanics of how people forecast.

Methods

Sample

The data used come from a panel study in progress (Tsimane' Amazonian Panel Study, TAPS) that started in 2002 (Leonard and Godoy 2008). The data used in this article come from all Tsimane' women (n=311) and men (n=326) ≥14 years of age in 13 Tsimane' villages along the Maniqui River, Beni department[1]. The only town and airport along the Maniqui River is San Borja. Villages differed in their closeness to San Borja (mean=25.90 km; standard deviation (SD)=16.70).

Dependent Variables: Collection of Wildlife and Planted Crops

We used behavioral spot observations (hereafter scans) (Sacket and Johnson 1998) and 24-h recall surveys done during the scan to gather data on the daily collection of wildlife and planted crops. For scans, we randomly selected 1 day each week and within the chosen day, randomly selected a block of 3 h to do the scan. For data collection, we split the chosen day into four blocks of time: (1) 7 A.M.–9 A.M., (2) 10 A.M.–12noon, (3) 1 P.M.–3 P.M., and (4) 4 P.M.–6 P.M.. The hours in a block were inclusive; for example, the first block of time from 7 A.M. until 9 A.M. went from 7:00 A.M. until 9:59 A.M.. During the scan we walked the village at a constant pace and coded what people were doing when we first spotted them. Half of the village was scanned 1 day and the other half on the next day. We did 7.27 days of scans each month (median=7.00 days; SD=1.73; total=80 days of scans for the 11 months of research), so we are able to capture variation in activities throughout the year. Note that we scanned people in and around the village, not in fields or forests.

After coding the behavior of the person spotted, we asked them about the type, provenience, and quantity of goods they had brought to the household during the previous 24 h. For people absent at the time of the scan, we asked a proxy respondent in the household about the current activity, collection of wildlife, and harvest of planted crops of the absent person during the 24 h before the interview. We later tested whether limiting the analysis to direct observations by the researchers (and excluding answers by proxy respondents) affected the main results.

We used the interview data collected during the scans to create two dependent variables: *foraging*=1 if the person reported bringing game, fish, or wild plants (except firewood) to the household during the 24 h before the interview and zero otherwise; and *farming*=1 if the person reported harvesting a planted crop during the 24 h before the interview and zero otherwise. The variable *farming* captures only food, whereas the variable *foraging* captures foods (whether plants or animals) plus wild resources used for other purposes (e.g., wild plants used for medicines). Since scan data were collected chiefly in or around the village, our data on labor allocation to weeding, planting, or various aspects of foraging are less reliable, which is why we do not do the analysis on time allocation among various stages of the foraging or farming cycle.

Explanatory Variable: Weather

We equate daily weather with the following: (1) the mean hourly temperature (C) in a day and (2) the total amount of rain (cm) in a day. Information on daily weather refers to the airport in the town of San Borja. Elsewhere (Godoy *et al*. 2008a, b) we show that daily mean hourly temperature and daily total rain in the town of San Borja reflect accurately daily mean hourly temperature and daily total rain in the villages of the study. Part A of Appendix 1 lists the sources of weather data and Part B is a step-by-step description of how we constructed the weather variables used in the regression analysis.

Because the weather today, the weather in the immediate past, and the weather in the immediate future are correlated, we control for *(a)* the weather during the 7 days *before today* and *(b)* for *today's* weather when estimating the effect of *future* weather over the next 1–7 days from today on today's collection of wildlife and on today's collection of planted crops.

Other Explanatory Variables

Other explanatory variables included: (1) body-mass index (BMI = body weight in kg/standing height in m^2) (measured quarterly) and (2) full sets of dummy variables for eight surveyors, 13 villages, 11 months of research, 7 days of the week, four 3-h time blocks in a day during which scans and surveys took place, and data quality (1 = direct observation, 0 = proxy respondent). BMI is a reliable anthropometric measure of short-term nutritional status for adults (Eveleth & Tanner 1990) and is used here as a proxy variable for objective health. All else held constant, we would expect people with normal BMI to be more successful at foraging than overweight or underweight people.

Analysis

We used multiple regressions with individual fixed effects, clustering by subjects, and robust standard errors. We

[1] The complete data and their documentation, along with publications from the Tsimane' Amazonian Panel Study (TAPS) project, are freely available for public use at the following address: http://people.brandeis.edu/~rgodoy/.

regress separately the two dichotomous dependent variables, *foraging* or *farming,* against the following explanatory variables: *(a)* the natural logarithm (hereafter log) of today's mean hourly temperature, *(b)* the log of today's total rain, *(c)* the log of the mean daily total rain for the 7 days before today, *(d)* the log of the daily mean of hourly temperature for the 7 days before today, *(e)* the mean weather for different number of days in the future, and *(f)* the variables 1 and 2 above. The regression results shown in Tables 2 and 3 contain the coefficients for *(e)*. The rows of Tables 2 and 3 capture the use of weather variables for different number of days in the future *(e)*. Regressions always include as controls the variables under *(a)-(d)* and *(f)*. STATA 10 (hereafter STATA) for Windows was used for the statistical analysis.

Tsimane' Subsistence

Subsistence

The Tsimane' number about 8,000 people and live in about 100 villages along riverbanks and logging roads, mostly in Beni department. Subsistence centers on hunting, collection of wild plants, fishing, and slash-and-burn farming (Vadez *et al*. 2004). Without irrigation Tsimane' depend on rain to produce crops. Rain also affects the likelihood of fishing, hunting, and collecting wild plants. Except for some Tsimane' who work as schoolteachers or for logging firms, most Tsimane' make their living by farming their own plots and by foraging. Elsewhere (Godoy *et al*. 2007) we document the low personal daily income (US$2.35–3.25) and the economic self-sufficiency of Tsimane'. Because Tsimane' are highly autarkic, their daily collection of wildlife and planted crops captures both production and consumption.

The percentage of observations from scans indicating that people had collected wildlife or planted crops on any given day were similar: 16.93% and 15.69% respectively. The variables *foraging* and *farming* had a Pearson correlation coefficient of 0.001 (p=0.909), suggesting that time spent in foraging does not reduce time spent in farming (and vice versa) and that Tsimane' carry out the two activities independent of each other.

One important aspect of agriculture that needs to be stressed to fully understand the regression results and conclusion presented later has to do with the flow of agricultural goods from the fields into the household in the Amazon. In temperate climates, the agricultural harvest is seasonal. On the other hand, in the Amazon rain forest where agriculture is composed of annual and perennial crops, the flow of agricultural goods from the fields into the households is steadier, taking place throughout the year. Among the Tsimane', the main annual crops such as rice and maize are typically harvested only once in a year, but other crops, such as plantains, manioc, and a wide range of tree crops are harvested year round. For this reason among the Tsimane' one can estimate the effect of future weather on day-to-day collection of planted crops. The exercise would be less meaningful in a temperate ecology where the harvest of crops takes place only during specific times of the year.

Weather

Figure 1 shows the mean total amount of rain for each month during 1943–2005 (the longest weather record available for San Borja) and for the period of this study (October 2002–August 2003). Both data sources show two seasons: a dry season between May and September and a wet season between October and April. The figure also shows that rain during the study period conformed to long-run trends, except for 2 months: December (2002) and January (2003) when total monthly rain levels were 75.21% and 62.13% below the long-term average for those months.

Figure 2a shows that mean monthly temperature during the study period tracked the long-term (1943–2005) trend of mean monthly temperature. The mean monthly temperature during the study period was 27.36°C, only 1.07°C

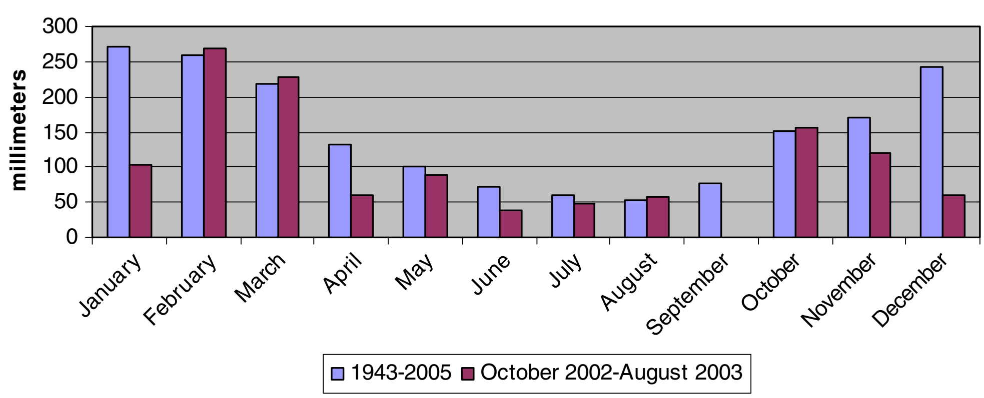

Fig. 1 Total monthly rain in the airport in the town of San Borja: 1943–2005 and October 2002–August 2003

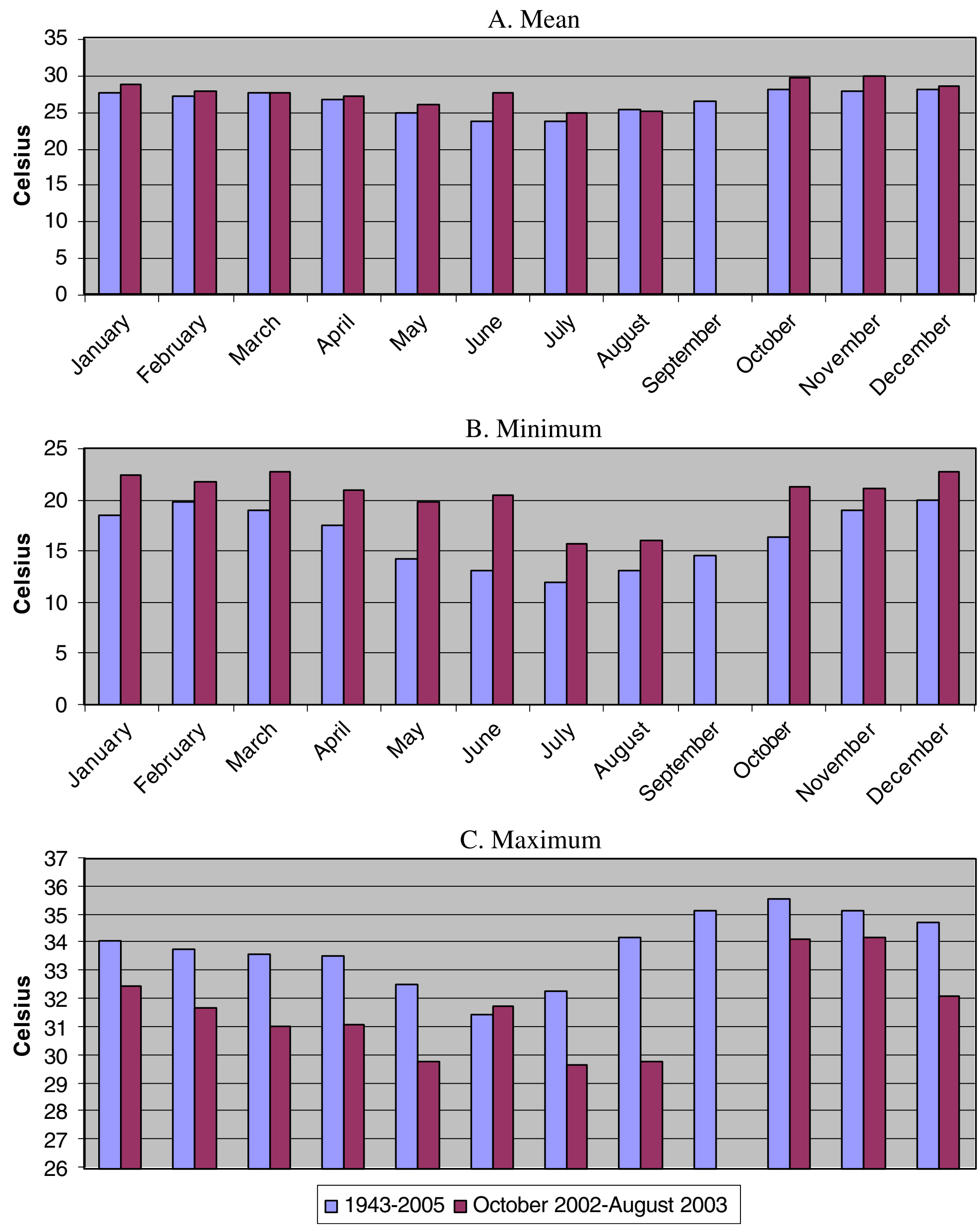

Fig. 2 Monthly temperature in the airport in the town of San Borja: 1943–2005 and October 2002–August 2003

or 4.06% higher than the mean monthly temperature during 1943–2005 (26.30°C). Figure 2b shows that the mean of the minimum monthly temperature during the study period was 20.41°C, 4.00°C or 24.38% higher than the mean of the minimum monthly temperature during 1943–2005 (16.41°C). Figure 2c shows that the mean of the maximum monthly temperature during the study period (31.62°C) was 2.23°C or only 6.58% lower than the mean of the maximum monthly temperature during 1943–2005 (33.85°C).

In sum, the weather data suggest that rain and temperature patterns during the study period tracked closely local rain and temperature patterns during 1943–2005. The partial exception was minimum temperature.

Seasons

Tsimane' clear the forest during the dry season, let the underbrush and logs dry before they burn the debris (Vadez *et al*. 2004) and then plant plantains and annual crops such as rice, maize, and manioc. Planting takes place between August and December, toward the end of the dry season and the beginning of the rainy season. If they cut the forest too early or if they wait too long (or if rains arrive early), the debris burns too poorly to: (a) deposit nutrients into the soil, (b) maximize the amount of space available for crops to grow, and (c) minimize the amount of labor required to prepare the field for planting (Baksh and Johnson 1990; Wilkie *et al*. 1999), thus affecting crop yields.

Starting in May with the onset of the dry season, many edible fruits in the forest ripen; this is the time when wild animals gain weight and provide ideal prey. The onset of the dry season corresponds with a greater frequency and duration of hunting expeditions. Some of the hunting expeditions are in groups and take many days. The dry season is also the time when Tsimane' use plant poison to fish, which they also often do in a group.

In Table 1 we show the percent of observations of people foraging or farming during scans (columns A–B) or who had collected wildlife or planted crops during the 24 h before the scan (columns D–E). The percentages in columns A–B suggest that during May–July Tsimane' were more likely to be foraging than farming, but with the onset of the planting season, from about September until November, time spent farming surpassed time spent foraging. The percentages in columns D–E suggest that dependence on foods from foraging and dependence on foods from farming varied across months. During October–December when Tsimane' prepare their farm plots, the probability of collecting wildlife was much higher than the probability of collecting planted crops. During February and March when they start to harvest annual crops (e.g., rice), collection of planted crops rose to 19.35% and 17.36% whereas collection of wildlife dropped to 14.17% and 10.83%.

Weather Forecasts

Most of the rules-of-thumb Tsimane' use to forecast weather center on the short term, or 1–3 days into the future. During open-ended, informal ethnographic interviews, Tsimane' said that the following signs today cue them that rains will arrive during the next 1–3 days: *(a)* one or more previous hot days, *(b)* the color, shape, proximity, and movement of clouds, *(c)* the behavior of some wild and domesticated animals, *(d)* halo around stars called *cava'-vare*, *(e)* a burial during the previous 1–2 days, and *(f)* holes on the ground made by ants.

During May–July, the *sur*—rains and unusually cold temperatures from the south—hit the Bolivian lowlands. Tsimane' use the flowering of some wild plants and the singing of some birds to forecast the *sur*'s arrival. During May–July, some Tsimane' listen on small, battery-operated transistor radios to reports of current weather from the department of Santa Cruz (which lies to the south-east of its territory) and, based on the arrival of the *sur* in Santa Cruz, estimate its approximate arrival in the Maniqui River. Tsimane' say that depending on wind velocity, the *sur* arrives in the Maniqui River between 6 h and 1 day after it reaches Santa Cruz. During 2002–2003, 255 households or 54.14% of the sample of households had transistor radios, but we do not know how many radios worked.

Except to forecast the *sur*, Tsimane' do not rely on weather reports from radio or from television stations because stations transmit current weather (rather than forecasts) for departments (rather than for smaller areas) and since rain in the Amazon varies within small areas (Moran *et al*. 2006) they are thus too general to be of use in the Maniqui River.

Tsimane' do not forecast the onset of the rainy season nor the amount of rain they expect during the coming agricultural cycle. We found no evidence that Tsimane' use the position of stars to forecast weather for the coming year, as do farmers in the Andean highlands (Orlove *et al*. 2000). Some Tsimane' said they expected oscillations of weather between years. For example, they expected an unusually rainy year to follow an unusually dry year.

Table 1 Percent of observations of Tsimane' over 14 years of age who were foraging or farming at the time of scans, or who reported having collected wildlife or planted crops during the 24 h before the scan, by month, October 2002–August 2003

Month	During scan person was:			In 24-h recall, person brought:		
	Foraging [A]	Farming [B]	Obs [C]	Wildlife [D]	Planted crops [E]	Obs [F]
2002						
October	11.30	21.53	469	13.48	9.05	519
November	11.74	13.10	954	23.96	12.42	1,014
December	15.66	6.92	664	20.62	14.50	703
2003						
January	11.46	7.31	916	15.43	15.33	1,004
February	7.76	13.48	927	14.17	19.35	1,023
March	5.91	21.11	947	10.83	17.36	1,071
April	7.74	17.58	813	15.31	18.81	914
May	11.01	6.13	554	17.11	16.93	555
June	13.51	6.46	866	19.73	16.90	917
July	11.57	5.57	950	17.58	14.68	1,103
August	6.80	4.25	235	20.26	11.76	306

Column A: person was hunting, fishing, or collecting feral plants other than firewood; column B: person was planting, harvesting, weeding, or processing any planted crop; column D: Person brought fish, game, or feral plants other than firewood into the household; column E: person brought a planted crop into the household

Tsimane' say that their expectation of tomorrow's weather informs what they will do today. For example, if they expect rain tomorrow, then today they weed so weeds will dry well and die from exposure to the hot sun, wash clothes so they dry well, collect firewood, harvest, plant, forage, and take day trips to nearby towns or villages. On rainy days, Tsimane' prefer to rest, prepare home-brewed alcoholic beverages, remove maize husks and grains from cobs, separate rice grains from chaff, do handicrafts, harvest plantains and manioc, and visit other households in the village.

Tsimane' say rain discourages hunting because: *(a)* it hampers a hunter's ability to see or hear wild animals, *(b)* it undermines the smelling acuity of hunting dogs, and *(c)* lack of sunlight erodes the hunter's ability to move through the forest. On rainy days, many wild animals hide, making it hard for hunters to spot their prey. Tsimane' said they could fish during a rainy day, but prefer not to do so because it is uncomfortable.

To assess whether there is a cultural consensus on the heuristics Tsimane' use to forecast weather, we did a pilot study during 2008 with 30 Tsimane' women and 30 Tsimane' men over 16 years of age living in villages outside of the panel study. We presented study participants with formal yes/no or true/false type questions (e.g., "If you see bird x fly north, then it will rain tomorrow"), and found high cultural consensus on local knowledge about weather forecasts.

Results

Table 2 shows two noteworthy findings. First, future weather during the next 3 days had a significant effect on the probability of collecting planted crops today but not on the probability of collecting wildlife today. For example, a 1% increase in the *(a)* total amount of rain tomorrow (column B1, row 1), *(b)* mean amount of daily total rain tomorrow and the day after tomorrow (column B1, row 2), and *(c)* mean amount of daily total rain during the next 3 days from today (column B1, row 3) reduced the probability of harvesting planted crops today by 0.03%, 0.05%, and 0.11%. A 1% increase in *(a)* mean hourly temperature tomorrow (column B2, row 1), *(b)* mean hourly temperature tomorrow and the day after tomorrow (column B2, row 2), and *(c)* mean hourly temperature during the next 3 days after today (column B2, row 3) increased the probability of harvesting planted crop today by 0.14%, 0.15%, and 0.21%. In contrast, future weather generally had no significant effect on today's collection of wildlife (columns A1–A2, rows 1–6).

Table 2 Effects of future rain and future temperature on the probability of collecting wildlife and planted crops today

Coefficient of future weather includes the mean of the log of total daily rain or the mean of the log of the daily mean of hourly temperature for the following no. of days after today:	No.	Dichotomous dependent variables for today's collection of:					
		A. Wildlife—foraging			B. Planted crops—farming		
		Coefficient of future weather:		R^2	Coefficient of future weather:		R^2
		1. Rain	2. Temp		1. Rain	2. Temp	
1: 1 day (tomorrow's weather)	7,099	0.005	0.019	0.001	−0.033[a]	0.148[a]	0.003
2: 2 days (weather tomorrow and day after tomorrow)	7,235	0.019	0.008	0.002	−0.050[a]	0.158[a]	0.005
3: 3 + 2 + 1	7,235	0.030	0.135	0.003	−0.112[a]	0.211[a]	0.005
4: 4 + 3 + 2 + 1	7,235	−0.003	0.125	0.002	−0.076	0.190	0.005
5: 5 + 4 + 3 + 2 + 1	7,235	−0.027	0.149	0.002	0.015	0.023	0.005
6: 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.050	0.102	0.002	−0.033	0.011	0.005
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.034	0.352[a]	0.002	−0.021	0.113	0.005

Regressions include individual fixed effects, clustering by subject, and robust standard errors. The table includes results of 14 regressions for two outcomes: seven for *foraging* (column A) and seven for *farming* (column B). For each of the two outcomes, we run seven regressions with various combinations of future periods as controls. In row "1" (tomorrow) we include and report the log of tomorrow's total rain and the log of the mean hourly temperature of tomorrow; in row "2" (weather tomorrow and the day after tomorrow) we include the mean amount of total daily rain of tomorrow and the day after tomorrow (expressed in logs) and the mean daily temperature of tomorrow and the day after tomorrow (expressed in logs, with daily mean temperature based on the mean of hourly measures for that day). Explanatory variables shown in the table include: *(1)* the log of future total rain (columns A1 and B1) and *(b)* the log of future daily hourly temperature (columns A2 and B2). Explanatory variables not shown but included in all regressions include: *(a)* the log of the mean daily total rain for the 7 days before today, *(b)* the log of the mean daily hourly temperature for the 7 days before today, *(c)* quarterly body-mass index (BMI) and household size, and *(d)* full set of dummy variables for eight surveyors, 13 villages, 11 months of research, 7 days of the week, four 3-h time blocks in a day during which surveys took place, and data quality (1 = direct observation, 0 = proxy respondent); R^2 is overall

[a] Significant <1%

Second, only future weather over the next 3 days from today affected the probability of harvesting planted crops today (columns B1–B2, rows 1–3); beyond 3 days into the future (columns B1–B2, rows ≥4), weather no longer affected the probability of harvesting planted crops today. This finding buttresses the ethnographic evidence presented earlier that Tsimane' weather forecasts center on the short term, typically 1–3 days.

Since we control for the weather today and for the weather during the 7 days before today, future weather must affect today's farming harvest through signs that cue Tsimane' on what the weather will be like over the short-term.

Robustness

In Table 3 we show the results of additional analysis to ensure the main conclusions do not hinge on how we carried out the main analysis shown in Table 2. The regressions of Table 3 are identical to the regressions of Table 2 except for the changes noted in the sub-headings. For Table 3 we reestimated the regressions of Table 2 using: (A) the day-to-day measures of rain and temperature for the previous 7 days from today instead of the mean daily temperature and the mean daily total rain for the previous 7 days from today, (B) minimum daily temperature and (C) maximum daily temperature instead of the mean of daily hourly temperature, (D) only the four main planted crops (rice, maize, manioc, and plantains) instead of any planted crop, (E) only fish and wild game and not wild plants, (F) only the months when the *sur* does not strike, (G) only observations with complete weather data for all future 7 days, and (H) only direct observations (i.e., exclude answers from proxy respondents). We next explain the rationale for introducing the changes.

We do (A) to ensure that our results are driven by future weather, rather than by an aspect of past daily weather that may correlate with future weather but that got lost when we averaged weather data for the 7 days before today. Recall from the previous discussion that Tsimane' use warm weather to predict rain, so it is possible that today's collection of planted crops or today's collection of wildlife responds more to maximum or to minimum daily temperature than to mean daily temperature. For this reason we do (B)–(C). We do (D)–(E) because some so-called wild plants may have been planted long ago (Huanca 1999), and some planted crops may have been planted so long ago that they could be considered wild. Limiting the analysis to the four main planted crops that are unlikely to be harvested in their wild state (D), and limiting the analysis to fish and wild game (E) allows us to obtain sharper results for the variables *farming* and *foraging*. Excluding the months when the *sur* strikes (May–July, inclusive) (F) allows us to remove the potential effect of weather reports from radio stations because Tsimane' are most likely to listen to such reports during the months when the *sur* arrives. The results of Table 2 could be biased by the missing observations for tomorrow's weather and for tomorrow's rain. As Table 2 shows, and as discussed in Appendix 2, the number of observations is lower for the first regression (row 1) than for all other regressions (rows 2–7) because of the missing values for tomorrow's weather. To address this issue, we reestimate the regressions of Table 2 using the same observations (n=7099) for all the regressions (G). Last, proxy respondents may have provided inaccurate answers about the absent person; results could change if we limit the analysis to events directly observed by researchers (H).

With two exceptions, the results of Table 3 support the main findings of Table 2. Using maximum temperature (C), limiting the analysis to the four main planted crops (D) and to fish and wild game (E), or using only observations without missing data for tomorrow's weather (G) confirmed the previous results that weather during the next 3 days from today had a significant effect on the collection of planted crops today but not on the collection of wildlife today. Excluding the months when the *sur* strikes (F) made four of the six coefficients under *farming* that were statistically significant in Table 2 become statistically insignificant at the 99% confidence interval or higher in Table 3 because of the reduction in sample size, but the sign of the weather coefficients under *farming* remained the same and the size of these coefficients did not change much. For instance, a 1%-increase in the total amount of rain tomorrow lowered the probability of collecting planted crops today by 0.03% in Table 2 ($p=0.007$)(column B1, row 1); if we limit the analysis to the months without the *sur*, the coefficient drops from 0.03% to 0.02% ($p=0.085$) (column B1, row 1). Limiting the analysis to direct observations (H) reduces the sample size for most regressions by 42% (from about 7235 to about 4190) and makes four of the six coefficients under *farming* that were statistically significant in Table 2 become statistically insignificant at the 1% level in Table 3, but the size of coefficients for temperature for tomorrow, for the day after tomorrow, and for the 2 days from today increased considerably—from 0.148, 0.158, and 0.211 in Table 2, to 0.180, 0.225, and 0.294 in Table 3 (H). Thus, though statistically weaker, the size of the effect of future weather on the collection of planted crops increases.

Section (A) of Table 3 produced weaker results and section (B) of Table 3 produced unexpected results compared with the results of Table 2. Using day-to-day measures of total rain and the day-to-day measures of mean hourly temperature for each of the 7 days before today (A) reduced the size of the coefficients for future weather in both *farming* and *foraging* and made them statistically insignificant. A comparison of the coefficients for future

Table 3 Sensitivity analysis of Table 2

Coefficient of future weather includes the mean of the log of total daily rain or the mean of the log of the daily mean of hourly temperature for the following no. of days after today:	No.	Dichotomous dependent variables for today's collection of:					
		A. Wildlife—foraging			B. Planted crops—farming		
		Coefficient of future weather:		R^2	Coefficient of future weather:		R^2
		1. Rain	2. Temp		1. Rain	2. Temp	
A. Log of daily rain and log of daily temperature for previous 7 days, with each day entered separately							
1: 1 day (control for tomorrow's weather)	6,909	−0.006	−0.026	0.020	−0.015	0.089	0.009
2: 2 days (tomorrow and day after tomorrow)	6,909	−0.019	−0.010	0.020	−0.030	0.119	0.009
3: 3 + 2 + 1	6,909	−0.006	0.062	0.021	−0.080*	0.197	0.010
4: 4 + 3 + 2+ 1	6,909	−0.016	−0.017	0.021	−0.059	0.214	0.009
5: 5 + 4 + 3 + 2 + 1	6,909	−0.021	−0.037	0.003	0.015	0.042	0.008
6: 6 + 5 + 4 + 3 + 2 + 1	6,909	−0.040	−0.121	0.019	−0.028	−0.048	0.008
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	6,909	−0.057	0.159	0.022	−0.027	0.156	0.009
B. Minimum daily hourly temperature instead of mean daily hourly temperature							
1: 1 day (control for tomorrow's weather)	7,099	0.003	0.115	0.001	−0.025	0.044	0.003
2: 2 days (tomorrow and day after tomorrow)	7,235	0.003	0.163*	0.002	−0.047*	0.035	0.005
3: 3 + 2 + 1	7,235	0.035	0.260*	0.005	−0.101*	0.079	0.006
4: 4 + 3 + 2 + 1	7,235	−0.009	0.296*	0.004	−0.071	0.110	0.005
5: 5 + 4 + 3 + 2 + 1	7,235	−0.062	0.281*	0.002	0.013	0.153	0.005
6: 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.089	0.258*	0.001	−0.025	0.245	0.005
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.086	0.223	0.001	−0.021	0.317*	0.005
C. Maximum daily hourly temperature instead of mean daily hourly temperature							
1 day (tomorrow)	7,099	0.001	−0.106	0.001	−0.028	0.189*	0.003
2 days (tomorrow and day after tomorrow)	7,235	0.014	−0.071	0.003	−0.056*	0.200*	0.005
3	7,235	0.027	0.049	0.003	−0.121*	0.260*	0.006
4	7,235	−0.023	0.064	0.002	−0.086*	0.221*	0.005
5	7,235	−0.061	0.110	0.002	−0.008	0.256*	0.005
6	7,235	−0.083	0.083	0.001	−0.074	0.287*	0.005
7	7,235	−0.070	0.104	0.001	−0.062	0.305	0.005
D. Farming limited to four main planted crops: maize, rice, manioc, and plantains							
1: 1 day (control for tomorrow's weather)	7,099	Not applicable			−0.035*	0.125*	0.002
2: 2 days (tomorrow and day after tomorrow)	7,235				−0.053*	0.139	0.005
3: 3 + 2 + 1	7,235				−0.113*	0.188*	0.005
4: 4 + 3 + 2 + 1	7,235				−0.080*	0.170	0.005
5: 5 + 4 + 3 + 2 + 1	7,235				0.004	0.022	0.004
6: 6 + 5 + 4 + 3 + 2 + 1	7,235				−0.040	0.020	0.005
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,235				−0.029	0.113	0.005
E. Wild plants excluded from foraging; only fish and wild game included							
1: 1 day (control for tomorrow's weather)	7,099	−0.0008	0.00008	0.006	Not applicable		
2: 2 days (tomorrow and day after tomorrow)	7,235	0.007	0.027	0.001			
3: 3 + 2 + 1	7,235	0.004	0.132	0.001			
4: 4 + 3 + 2 + 1	7,235	−0.032	0.129	0.001			
5: 5 + 4 + 3 + 2 + 1	7,235	−0.044	0.091	0.001			
6: 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.048	0.051	0.001			
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.052	0.160	0.001			
F. Limited to August-April (inclusive), the months without *sur*							
1: 1 day (control for tomorrow's weather)	5,355	0.002	0.030	0.008	−0.027	0.134	0.006
2: 2 days (tomorrow and day after tomorrow)	5,355	0.031	−0.012	0.009	−0.057*	0.192	0.006

Table 3 (continued)

Coefficient of future weather includes the mean of the log of total daily rain or the mean of the log of the daily mean of hourly temperature for the following no. of days after today:	No.	Dichotomous dependent variables for today's collection of:					
		A. Wildlife—foraging			B. Planted crops—farming		
		Coefficient of future weather:		R^2	Coefficient of future weather:		R^2
		1. Rain	2. Temp		1. Rain	2. Temp	
3: 3 + 2 + 1	5,355	0.051	0.158	0.008	−0.135*	0.175	0.008
4: 4 + 3 + 2 + 1	5,355	0.025	0.038	0.008	−0.095	0.214	0.007
5: 5 + 4 + 3 + 2 + 1	5,355	0.004	0.126	0.009	−0.002	−0.047	0.006
6: 6 + 5 + 4 + 3 + 2 + 1	5,355	−0.057	−0.009	0.008	−0.076	−0.147	0.006
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	5,355	0.013	0.200	0.009	−0.063	−0.079	0.006
G. Excluding days with missing weather for tomorrow to equalize the sample size of observations across regressions							
1: 1 day (control for tomorrow's weather)	7,099	0.005	0.019	0.001	−0.033*	0.148*	0.003
2: 2 days (tomorrow and day after tomorrow)	7,099	0.024	−0.011	0.001	−0.055*	0.169*	0.003
3: 3 + 2 + 1	7,099	0.037	0.109	0.001	−0.118*	0.225*	0.003
4: 4 + 3 + 2 + 1	7,099	0.002	0.085	0.001	−0.082*	0.212	0.003
5: 5 + 4 + 3 + 2 + 1	7,099	−0.018	0.118	0.001	0.008	0.037	0.003
6: 6 + 5 + 4 + 3 + 2 + 1	7,099	−0.038	0.058	0.001	−0.041	0.035	0.003
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,099	−0.025	0.309*	0.001	−0.032	0.151	0.003
H. Analysis limited to direct observations by researchers (excludes data from proxy respondents)							
1: 1 day (control for tomorrow's weather)	4,130	0.021	−0.051	0.014	−0.021	0.180	0.001
2: 2 days (tomorrow and day after tomorrow)	4,190	0.040	−0.067	0.001	−0.052	0.225	0.001
3: 3 + 2 + 1	4,190	0.045	0.069	0.007	−0.108*	0.294*	0.001
4: 4 + 3 + 2 + 1	4,190	0.019	0.041	0.007	−0.045	0.279	0.001
5: 5 + 4 + 3 + 2 + 1	4,190	−0.008	0.088	0.001	0.067	0.138	0.001
6: 6 + 5 + 4 + 3 + 2 + 1	4,190	−0.037	0.052	0.007	0.002	0.155	0.001
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	4,190	−0.024	0.402*	0.001	0.035	0.280	0.001

Same notes and definitions as Table 2. A: Instead of using the log of the mean hourly temperature and the log of mean daily total rain for the 7 days before today, we introduce the log of mean daily hourly temperature and the log of daily total rain for each of the 7 days before today; this produces 14 additional explanatory variables

rain and future temperature for one, two, and 3 days from today (rows 1–3) between Tables 2 and 3 (section A) shows that the coefficients for rain fell by an average of 41.04% and that the coefficients for temperature fell by an average of 23.73%. The reduction in the size of the coefficients suggests that (1) the sign of the indirect effect from excluding day-to-day weather variables for the 7 days before today in Table 2 is positive and (2) the loss of statistical significance likely could have resulted from the multicollinearity of including 14 additional explanatory variables and reducing the sample size from 7235 observations to 6909 observations.

The use of minimum temperature (B) suggests that future minimum daily temperature 2–6 days from today has a significant positive effect on the collection of wildlife; on average, an increase of 1% in minimum temperature during the next 2–6 days from today increased the probability of collecting wildlife today by 0.16–0.29% (section B, column A2, rows 2–7). In the regression with *farming* as a dependent variable the use of minimum daily temperature made the coefficients for daily minimum temperature for the next one, two, and 3 days from today (section B, column B2, rows 1–3) about 70% smaller than the coefficients for the mean of daily temperature for the next one, two, and 3 days from today in Table 2. In the regressions with *farming* as a dependent variable the use of minimum daily temperature did not affect the coefficients for future rain during the next two and 3 days from today (section B, column B1, rows 2–3); these coefficients remained essentially unchanged from Table 1 and statistically significant.

In sum, the results of the additional analysis generally support the main finding of Table 2 that rain and temperature over the next 3 days from today affects the probability of collecting planted crops today more than the probability of collecting wildlife today.

Extensions

So far we have presented evidence suggesting that future weather affects the probability of collecting planted crops more than the probability of collecting wildlife today, but how does *today's* weather affect the probability of today's collection of planted crops or wildlife after conditioning for past and future weather?

In Table 4 we show the effects of today's total rain and today's mean hourly temperature on the probability of collecting planted crops or collecting wildlife today; the coefficients in Table 4 come from the regressions of Table 2. Table 4 shows three important findings.

First, today's mean hourly temperature affected the probability of collecting wildlife today (column A2). Without controlling for future temperature (row 0, column A2) we see that a 1% increase in today's mean hourly temperature increased by 0.26% the probability of collecting wildlife today. Controlling for tomorrow's total rain and for tomorrow's mean hourly temperature (row 1, column A2) or controlling for the mean total daily rain and for the mean daily temperature of tomorrow plus the day after tomorrow (row 2, column A2) did not change the magnitude of the effect; a 1% increase in today's mean hourly temperature increased the probability of collecting wildlife today by 0.26–0.27%. Controlling for the mean amount of daily total rain and for the mean daily hourly temperature for the next 3, 4, 5, 6, and 7 days from today lowered the effects of today's mean hourly temperature on the probability of collecting wildlife today (rows 3–7, column A2). Whereas a 1% increase in today's mean hourly temperature increased the probability of collecting wildlife today by about 0.26% if we control for the mean amount of total daily rain and for the mean hourly temperature for the next 1–2 days in the future (rows 1–2, column A2), the same increase in today's mean hourly temperature increased the probability of collecting wildlife today by about 0.22% if we control for weather 3–7 days into the future (rows 3–7, column A2). On average, a 1% increase in today's mean hourly temperature raised the probability of collecting wildlife today by about 0.24% (average of estimate of rows 0–7, column A2).

Second, a 1% increase in today's total rain lowered by about 0.01% the probability of collecting wildlife today (0.01%=mean estimate of rows 0–7, column A1) and it lowered by about 0.02% the probability of collecting planted crops today (0.02%=mean estimate of rows 0–7, column B1), but results were generally statistically insignificant at the 99% confidence level or higher.

Third, today's mean hourly temperature or today's total rain generally did not affect the probability of collecting planted crops today (columns B1 and B2).

In sum, after controlling for weather during the 7 days before today, and for the weather for periods of time into the future that ranged from 1 day to 7 days, we find that the probability of collecting wildlife responds to today's mean hourly temperature (but not to today's total rain). In contrast, the probability of collecting planted crops today remained largely unaffected by today's mean hourly temperature or by today's total rain.

Table 4 Effects of (1) the log of today's total rain and (2) the log of today's mean hourly temperature on the probability of collecting wildlife or planted crops today: results of individual fixed-effect regressions

Controlling for the mean of the log of daily rain and the mean of the log of daily hourly temperature for the following no. days after today:	No.	Dichotomous dependent variables for today's collection of:					
		A. Wildlife—foraging			B. Planted crops—farming		
		Coefficient of log of today's:		R^2	Coefficient of log of today's:		R^2
		1. Total rain	2. Mean hourly temperature		1. Total rain	2. Mean hourly temperature	
0: 0 (today; no control for future weather)	7,235	−0.010	0.261*	0.002	−0.021	0.030	0.005
1: 1 day (control for tomorrow's weather)	7,099	−0.012	0.277*	0.001	−0.026*	−0.116	0.003
2: 2 days (tomorrow and day after tomorrow)	7,235	−0.011	0.268*	0.002	−0.024	−0.084	0.005
3: 3 + 2 + 1	7,235	−0.020	0.216*	0.003	−0.022	−0.057	0.005
4: 4 + 3 + 2 + 1	7,235	−0.014	0.224*	0.002	−0.021	−0.048	0.005
5: 5 + 4 + 3 + 2 + 1	7,235	−0.012	0.214*	0.002	−0.023	0.031	0.005
6: 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.009	0.228*	0.002	−0.019	0.018	0.005
7: 7 + 6 + 5 + 4 + 3 + 2 + 1	7,235	−0.021	0.230*	0.002	−0.024	0.017	0.005

Same notes as Table 2.

Limitations

This study contains at least two limitations. First, our data are not refined enough to allow us to estimate how future weather might affect different stages of the farming or of the foraging cycle. The dependent variables in Tables 2, 3 and 4 refer only to the collection of wildlife or to the collection of planted crops and come from 24-h recall surveys. Foraging requires several steps, such as pursuit and collection. Farming also requires several steps, such as cutting and burning the forest, planting, weeding, and harvesting. Future weather might have different effects on these steps. Second, it is possible that weather over the next 1–3 days has an impact on the harvest of planted crops, but only in regions such as the Amazon with abundant perennial crops (e.g., plantains, tree crops). The effect of short-term weather forecasts on the harvest of planted crops might be very different in areas without (or with less) perennial crops or in areas that depend heavily on planted annual crops.

Discussion and Conclusions

We return to our original question: To what extent do actual events in the future determine current behavior after conditioning for the role of past and current confounders? Drawing on our data from the Tsimane', we find that rain and temperature over the next 3 days from today affect the probability of collecting planted crops today more than the probability of collecting wildlife today. This could have happened if future weather correlated with past and current weather, but since we conditioned for past and for current rain and temperature, future weather must affect today's farming harvest through signals that tell Tsimane' what future weather will be like. Although we have not explicitly measured or incorporated forecasting in the regression analysis, our results are in accord with prior work by anthropologists (discussed in the introduction) who have found that rural people in low-income nations tend to make reasonably accurate short-term weather forecasts.

How do Tsimane' Forecast Weather?

The finding that future weather affects the probability of collecting planted crops today raises the question of how Tsimane' forecast weather. The question lies beyond the scope of this paper and we have no direct data to address it. This said, we can rule out the hypothesis that Tsimane' forecast weather accurately because they have locally developed cultural knowledge because we used an individual fixed-effect regression model. In so doing, we swept away any attribute that remained fixed in the individual during the study period. The stock of local knowledge of weather (or cultural competence) for an individual is unlikely to have changed over such a short period of time. The fixed-effect regression also purges the estimates of the possible effects of visual acuity or the innate ability to 'feel' tomorrow's weather.

In our model, accuracy cannot reflect fixed attributes. Rather, accuracy must reflect attributes that *change over time*. One promising line of research, suggested by Tucker (2007), traces accuracy to on-the-spot judgments about future weather, judgments that reflect cultural theories of covariation of events, strength of individual memory, and other factors that change over time. For instance, a Tsimane' might know that the presence of a bird flying in a certain direction predicts well rain tomorrow, but the Tsimane' might misclassify the bird or the bird's flight direction on particular days. Since weather forecasts rest on several heuristics—for instance, not only a certain type of bird flying but also the presence of a critical amount of particular ants—then Tsimane' must use their memory to weigh and harmonize many strands of evidence before making a final judgment about future weather. Furthermore, Tsimane' might look at their neighbors for confirmation on what to expect. If one sees many people taking umbrellas to work, then one can be more confident in forecasting rain later in the day. Just by chance, on some days people might see neighbors and make more informed forecasts about the weather, but on other days they might have to rely on their own knowledge and observations. We remove some of this noise by using dummy variables for communities, days, and time-of-day, but it is possible that some of the information gathering about the future takes place by watching only selected individuals over a smaller geographic focus (e.g., a small cluster of households within a village). In short, explanations of the accuracy of weather forecasts probably go far beyond local weather knowledge, to more complex psychological processes and biases about how people make decisions under uncertainty.

On the Differential Vulnerability of Foraging and Farming to Current Weather

We found that today's mean hourly temperature (but not today's total rain) affected the probability of collecting wildlife today, but today's weather did not affect the probability of collecting planted crops today. This result suggests that today's success at collecting wildlife is more sensitive to today's weather than today's success at collecting planted farm crops. The finding that today's farming output is protected against ordinary daily weather that is not extreme (e.g., floods, droughts) is consistent with a large body of empirical work in rural areas of low-income nations suggesting that small-scale farmers protect their food production well against small idiosyncratic adverse shocks (see Godoy *et al*. 2008a, b for recent reviews). On the other hand, the greater responsiveness of the foraging harvest to today's weather after conditioning for future and for past weather suggests that foraging might be more vulnerable to climate perturbations than farming. If farming protects daily food consumption better than foraging against daily weather, then this might provide one more stimulus to increase dependence on farming.

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Appendix 1: Sources of Weather Data and Construction of Weather Variables

A. Sources for Weather Data

1) Source: National Oceanic & Atmospheric Administration (NOAA); US department of Commerce
a) Home page. http://www.noaa.gov/
b) Data downloaded from this link. http://www.ncdc.noaa.gov/oa/ncdc.html (Data link)
c) For free data. http://www.ncdc.noaa.gov/oa/mpp/freedata.html
d) Scroll down to free data J- Surface data- Global summary of the day.
   - Select the country
   - Choose the station of interest (in this case San-Borja, Rurrenabaque, and Trinidad)
e) Data from Jan 2002 to Dec 2003 was downloaded.
2) **Address:**
   National Climatic Data Center
   Federal Building
   151 Patton Avenue
   Asheville NC 28801-5001
   1-828-271-4800
   FAX: 1-828-271-4876
   Email: ncdc.info@noaa.gov
   All contact information for various departments can be access through this link
   http://www.ncdc.noaa.gov/oa/about/ncdccontacts.html
3) **Coding**
   First record—header record.
   All ensuing records—data records as described below.
   All 9's in a field (*e.g*., 99.99 for PRCP) indicates no report or insufficient data.

FIELD	POSITION	TYPE	DESCRIPTION
STN	1–6	Int	Station number (WMO/DATSAV3 number) for the location.
WBAN	8–12	Int	WBAN number where applicable—this is the historical "Weather Bureau Air Force Navy" number—with WBAN being the acronym.
YEAR	15–18	Int	The year
MODA	19–22	Int	The month and day
TEMP	25–30	Real	Mean temperature for the day in degrees Fahrenheit to tenths. Missing=9999.9 (Celsius to tenths for metric version.)
MAX	103–108	Real	Maximum temperature reported during the day in Fahrenheit to tenths—time of max temp report varies by country and region, so this will sometimes not be the max for the calendar day. Missing=9999.9 (Celsius to tenths for metric version.)
Flag	109–109	Char	Blank indicates max temp was taken from the explicit max temp report and not from the 'hourly' data. * indicates max temp was derived from the hourly data (i.e., highest hourly or synoptic-reported temperature)
MIN	111–116	Real	Minimum temperature reported during the ay in Fahrenheit to tenths—time of min temp report varies by country and region, so this will sometimes not be the min for the calendar day. Missing=9999.9(Celsius to tenths for metric version.)
Flag	117–117	Char	Blank indicates min temp was taken from the explicit min temp report and not from the hourly' data. * indicates min temp was derived from the hourly data (i.e., lowest hourly or synoptic-reported temperature)
PRCP	119–123	Real	Total precipitation (rain and/or melted snow) reported during the day in inches and hundredths; will usually not end with the midnight observation—i.e., may include latter part of previous day. .00 indicates no measurable precipitation (includes a trace). Missing=99.99 (For metric version, units = millimeters to tenths and missing=999.9.

			Note: Many stations do not report ‘0’ on days with no precipitation—therefore, ‘99.99’ will often appear on these days. Also, for example, a station may only report a 6-h amount for the period during which rain fell. See Flag field for source of data.
Flag	124–124	Char	A = 1 report of 6-h precipitation amount.
			B = Summation of 2 reports of 6-h precipitation amount.
			C = Summation of 3 reports of 6-h precipitation amount.
			D = Summation of 4 reports of 6-h precipitation amount.
			E = 1 report of 12-h precipitation amount.
			F = Summation of 2 reports of 12-h precipitation amount.
			G = 1 report of 24-h precipitation amount.
			H = Station reported ‘0’ as the amount for the day (e.g., from 6-h reports), but also reported at least one occurrence of precipitation in hourly observations—this could indicate a trace occurred, but should be considered as incomplete data for the day.
			I = Station did not report any rain data for the day and did not report any occurrences of precipitation in its hourly observations—it’s still possible that rain occurred but was not reported.

The NCDC Climate Services Branch (CSB) is responsible for distribution of NCDC products to users. NCDC’s CSB can be contacted via the following phone number, internet address, or fax number:

Telephone number: 1-828-2714800

Fax number: 1-828-2714876

Internet address: ncdc.orders@noaa.gov

4) Methods used to impute the missing values

- Daily temperature comes from hourly records of temperature. Daily temperature was converted to centigrade using the following formula,
  T in C = [(T in F-32)/9]*5
- Rain data refers to the total for a given day and was given in inches; multiplied by 2.54 to convert into centimeters
- If San Borja had a missing value, we imputed the mean value from Trinidad and Rurrenabaque, two nearby towns. Recent publications contain discussion of imputation methods for missing weather data (Godoy *et al*. 2008a, b).

B. Construction of Weather Variables

Log transformation. We took the natural logarithm (hereafter log) of daily temperature. We added +1 to daily total rain before taking the log of daily rain to avoid producing missing values for days without rain.

First step: measures of future weather day by day. We took the log of the mean daily hourly temperature and the log of daily total rain for 1, 2, 3, 4, 5, 6, and 7 days *after* today. Day 1 after today refers to tomorrow, day 2 after today refers to the day after tomorrow, etc. The first step produced a total of 14 variables for *future* weather, seven variables capturing daily total rain for each of the next 7 days after today and another seven variables capturing the mean of hourly temperature for each of the next 7 days after today.

Second step: future weather—mean values. Drawing on the values from the first step we took the mean of the log of daily rain and the mean of the log of daily temperature for seven future periods. For example, we estimated *(1)* the mean amount of total daily rain (in logs) for tomorrow (day 1), *(2)* the mean amount of total daily rain (in logs) for tomorrow and the day after tomorrow (mean of day 1 and day 2 after today), or *(3)* the mean amount of total daily rain (in logs) for the next 7 days from today (mean of days 1 + 2 + 3 + 4 + 5 + 6 + 7 after today). This step produced 14 additional variables for the mean of weather variables for different periods of time in the future (e.g., mean temperature of tomorrow and the day after tomorrow; mean temperature of the next 7 days).

Third step: measures of past weather day by day. We took the log of the mean daily hourly temperature and the log of daily total rain for 1, 2, 3, 4, 5, 6, and 7 days *before* today. In the previous sentence, day 1 before today refers to yesterday, day 2 before today refers to the day before yesterday, etc. The third step produced a total of 14 variables for *past* weather, seven variables capturing daily total rain for each of the previous 7 days before today and another seven variables capturing the mean of hourly temperature for each of the previous 7 days before today.

Fourth step: past weather—average of last 7 days before today. Drawing on the values from the third step, we took the mean of the log of rain and the mean of the log of temperature for the 7 days before today. The fourth step produced two variables for past weather: the mean daily total rain and the mean daily temperature for the 7 days before today.

Fifth step: today’s weather. We took the log of today’s total rain and the log of today’s mean hourly temperature.

In the regressions we only use the variables from the second, fourth, and fifth steps; the variables from the first and third step were used as inputs to construct variables in the other steps. All the variables from the fourth and the fifth step appear in all regressions; that is, in all regressions we control for the weather during the previous 7 days before today (*fourth step*) and for today's weather (*fifth step*). Among the variables of the second step (*future weather*), only some variables are entered in each regression, as shown in the first columns of Tables 2, 3 and 4.

Appendix 2: A Note on the Sample Size of the Regressions

In Table 2, the sample size of the regressions with tomorrow's weather as an explanatory variable (row 1) is smaller (n=7099) than the sample size (n=7235) of the other regressions (rows 2–7). The difference arises from the way STATA computes the mean of variables across rows. The STATA command "egen x = rowmean (×1 ×2 ×3)" produces the mean of x1, x2, and x3; if the value of one variable is missing, STATA estimates a mean for the remaining two variables. Nine days had missing data for tomorrow's rain or for tomorrow's temperature, and for these days the mean rain and the mean temperature for tomorrow were set to missing values. There were no days that had two or more consecutive future days of missing values for weather variables. Therefore, the mean of the weather variables for days 1 + 2, days 1 + 2 + 3, days 1 + 2 + 3 + 4, days 1 + 2 + 3 + 4 + 5, days 1 + 2 + 3 + 4 + 5 + 6, and days 1 + 2 + 3 + 4 + 5 + 6 + 7 into the future had more observations than the variable for only tomorrow's weather (mean of day 1) since the mean of a weather variable for two or more days into the future always produced a non-missing value, even if one of the days in the future had a missing value. In the article we show that the main results do not change if we exclude the observations with missing data for tomorrow's weather and run all the regressions with the same number of observations.

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