Title:

Modern Times: Longitudinal Study of Toba/Qom Communities Reveals Delay and Shortening of Sleep in Real-Time Across Electrification

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Abstract:

Electric light has profoundly altered human sleep by enabling extended activity after dark. To investigate its effects, we studied native Toba/Qom communities in northern Argentina from 2012 to 2024, comparing rural groups newly introduced to electricity with semi-urban groups with a continuous access to it. Fitting linear models over 12,000+ sleep events from 156 participants across this period, we examined changes in sleep dynamics over time. While both groups presented larger delays in sleep timing and reductions in sleep regularity, rural communities lost a full hour of sleep in only ten years. Changes in urban areas suggest additional influences from modern technologies beyond electric light, such as smartphones and the internet. Such huge changes in such a short period of time highlight the powerful role of electricity and technologies in shaping human sleep and underscore the importance of carefully managing technological transitions in underserved communities.

MAIN TEXT

Introduction

The discovery of electric power and thus the invention of the electric bulb revolutionized human life in ways that are impossible to quantify. One of its main effects was the conquest of the night hours, historically reserved for sleep, through the creation of lit environments safe from the perils of darkness. Electric light allowed for the extension of wakefulness and chores into the evening hours and, eventually, the birth of the 24/7 society of work and entertainment in the current hyper-industrialized world. This process has not only significantly delayed sleep times but has also likely driven a reduction in sleep duration. A poll by Gallup published in April 2024 reveals that Americans report they sleep markedly less than 80 years ago (*1*), and a systematic review of available children's data from 1905 to 2008 suggests a decrease in daily sleep of 1 hour in this period (*2*). Nevertheless, whether sleep has shortened with industrialization remains controversial, and, indeed, a recent analysis of published sleep data suggests that the opposite may be true (*3*).

In order to study the ways in which electric light has affected human behavior, we need to be able to compare the populations in which electricity is available to different degrees, while otherwise having similar genetic, historical, and cultural backgrounds. Pre-industrial societies with these characteristics offer unique opportunities to investigate the impact of electric light on sleep patterns, as they usually display differential access to electricity, high levels of exposure to the natural environment, weaker scheduling impositions, and rely more on environmental and ecological time references (*4–7*).

Our group is focused on the study of native Western Toba/Qom populations in the northern region of Argentina (*8*). These people, formerly hunter-gatherers, remain a very isolated and underprivileged group spread in the Formosa province, relying mostly on government assistance for subsistence. For the last 13 years, we have been studying sleep and circadian rhythms of both rural and urban-adjacent Toba/Qom communities, allowing us to contrast the behavior of communities in which the most relevant distinguishing characteristic is their access to electricity. Our work has shown that, indeed, urban Toba/Qom displayed later sleep onsets and shorter sleep duration than rural communities with no access to electricity (*9*). This correlation between electric light and delayed sleep has also been reported by several other groups studying pre-industrial communities around the world (*10–14*).

Since we started working with Toba/Qom communities in 2012, electricity has been progressively introduced to most rural areas in this region of the country, including the most isolated settlements (Fig. 1). Since such efforts started around 2016, all the communities we have worked with are now connected to the electric grid, and at the time of writing this paper, every single family we have worked with has electricity in their homes. Television sets and smartphones, as well as internet connections, while in very limited supply, are already available to many families.

We have longitudinally monitored sleep patterns through wrist-actigraphy in these Toba/Qom communities at different seasons and time points since 2012, generating a dataset of over 12,000 sleep records. This dataset represents a unique opportunity to assess the impact of the introduction of electricity on the sleep of these communities in real-time. The study we present here provides a close insight into the history of human sleep patterns in developing pre-industrial communities, highlighting the profound impact of modern technology on human behavior.

Results

Our sleep dataset from Toba/Qom communities includes over 12,000 sleep events recorded through wrist-actigraphy between 2012 and 2024 from a total of 156 participants (94 in the rural group, 62 in the urban group). Table S1 details the number of participants, recorded events, and age and sex composition of all data according to community, year, and dates when it was

collected. During this period, starting around the year 2016, electricity was progressively introduced in the rural communities in the Vaca Perdida and neighboring areas. Fig. 1.A and Fig. S1 show night radiance data from the NASA VIIRS instrument around our urban study site (Barrio Toba in Ingeniero Juárez) and the epicenter of the rural site (the Vaca Perdida settlement). While not exactly quantifying the availability of electric light in and around each house, it illustrates the landmarks of the introduction of electricity in the rural areas, as well as the marked contrast in development between the two study areas. While not a single participant from either community owned a smartphone by 2018, 52% of the participants in our studies had their own smartphone by October, 2024 (12/22 and 19/37 in the Urban and the Rural groups, respectively; 3 did not answer); and from those who did not, over a half said they would often borrow one (17/28 overall). About 45% of participants had access to a TV and/or a computer at their homes (9/22 and 19/40, respectively; one did not answer). Even in very remote rural areas, where cell phone coverage is extremely limited, some participants are able access the internet through free public Wi-Fi hotspots. Throughout this period of significant transformations for the rural Toba/Qom, we detect a progressive delay in sleeping times both at the individual and community level (Fig. 1.B).

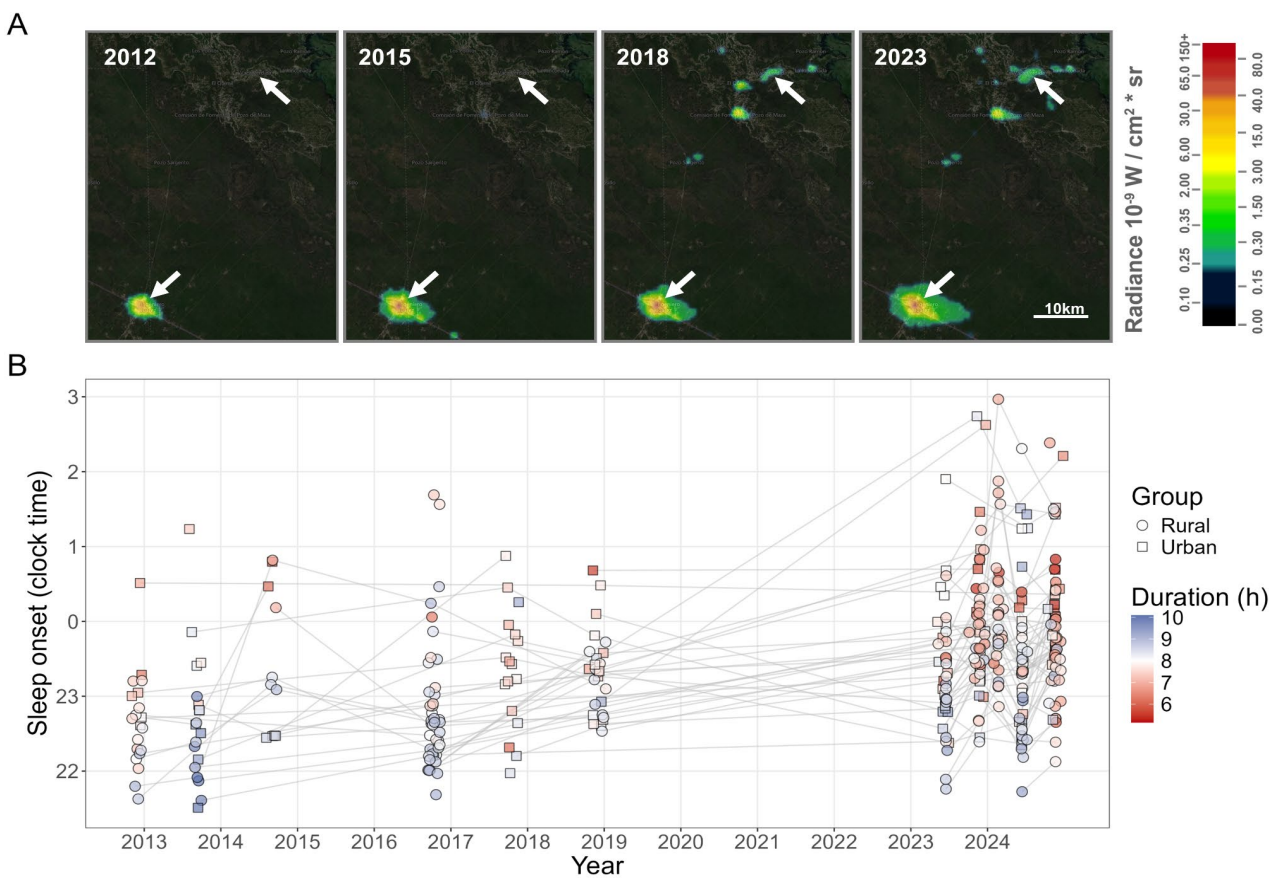

Fig. 1. Evolution of night light pollution and sleep from 2012 to 2024 in both rural and urban areas. (A) Radiance Day/Night Band levels measured by NASA's VIIRS instrument in the geographic regions of Ingeniero Juárez (bottom-left arrow) and Vaca Perdida (top-right arrow) over the years, obtained from Jurij Stare's Light Pollution Map. **(B)** Summary of sleep start times and duration. Each marker indicates the mean time of sleep start for a participant at a single data collection campaign, with gray lines connecting repeated measurements. Fill colors represent the mean sleep duration, and shapes indicate the participant's group.

In order to study the underlying factors behind these observed changes in sleep, we fit linear mixed-effects models (LMEMs) to all night sleep timing variables, including group (urban or rural; i.e continuous or progressive access to electricity), calendar year, and photoperiod length, along with their double and triple interactions, as well as sex and age, and type of day (*workday* or *free-day*) as fixed effects, and including participants as a random factor. After fitting the models, we compared the model-predicted values across time for the photoperiod length values of 11h (i.e. Winter) and 13h (Summer); with the age value set at 22 years old (the median of participants' ages across all data collection campaigns) and all the other fixed factors set at their average level. Since age was not included in any interaction in our models (other than with sex), fixing an age value only influences the absolute value of the predictions but not the predicted differences between groups or across time (i.e., the predicted difference in sleep onset between an urban participant and a rural participant at a given year is the same whether they are both 22 years old or 40 years old). Estimates for all LMEMs in this study are presented in Table S2, and post-hoc contrasts in Table S3. Effect sizes are expressed in absolute units of the measured variables (along with 95% confidence intervals for model estimates and predictions, and ± standard errors for post-hoc contrasts). For an easier appreciation of the magnitude of changes across time, we indicate the average predicted values and the magnitude of changes in a ten-year span from 2013 to 2023. Fig. 2 presents a summary of the model-predicted values for both Toba/Qom communities across the years and according to season.

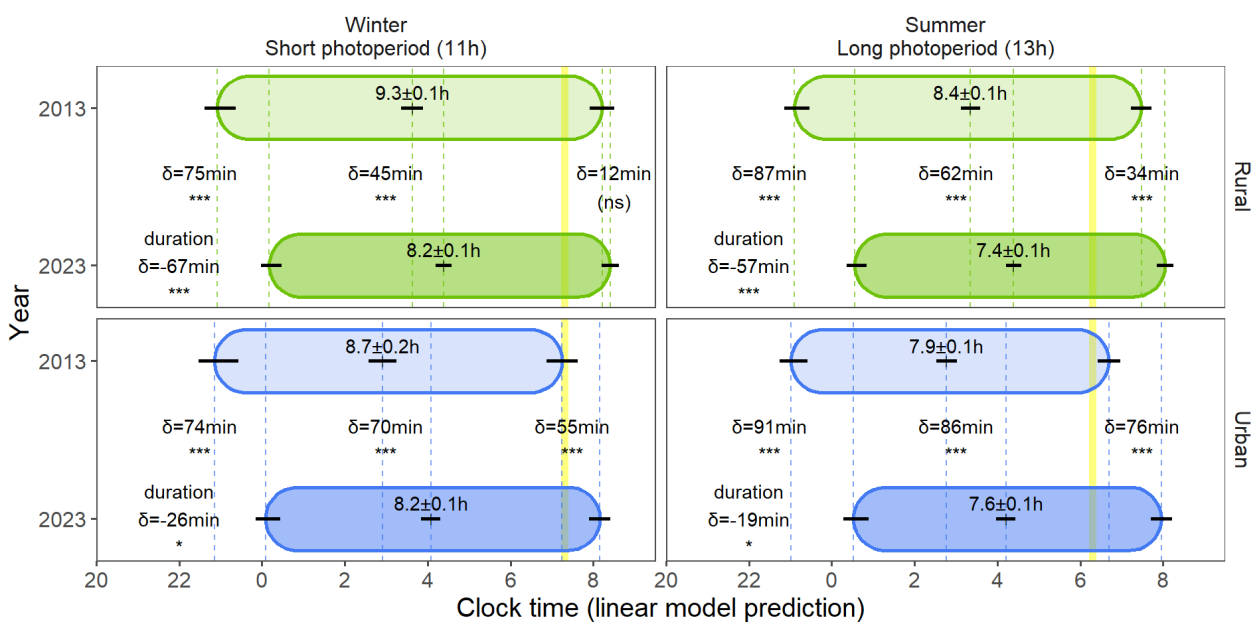

Fig. 2. Evolution of sleep patterns from the rural (top row) and urban (bottom row) Toba/Qom communities under different natural photoperiod lengths. Plotted are the predictions for a 22-year-old participant (averaged for sex and type of day) from linear models including random effects. Predictions for only two timepoints across a 10-year span (2013 to 2023) are displayed for simplicity. Vertical dashed lines were drawn for the start, end, and midpoint of sleep, and horizontal black lines represent the standard error of these predictions. Predicted sleep duration in hours (±SE) is also indicated within each box. Differences are indicated for all sleep variables, and asterisks indicate statistically significant changes across the 2013-2023 span modelled. The yellow vertical line represents the approximate time of dawn in each season. * $p<0.05$, ** $p<0.01$, *** $p<0.001$ (Tukey-corrected for multiple comparisons)

Sleep duration was differentially reduced throughout the years in both communities. The rural community displayed a striking reduction of sleep time across time in both seasons, which was over twice as large as that in the urban community (Fig. 3.A, Table S3). Sleep duration in the rural community was shortened by 67±8 min during the winter season (from 9.31h in 2013 to 8.20h in 2023; $t=-8.29$, $p<0.001$) and 56±6 min in the summer season (from 8.40h to 7.44h; $t=-9.57$, $p<0.001$). The urban group showed smaller, albeit significant, reductions in sleep time in both seasons (from 7.59h in 2013 to 7.26h in 2023 in the summer; $\Delta= -19\pm8$ min, $t=-2.48$, $p=0.013$; and from 8.33h to 7.91h in the winter; $\Delta= -26\pm10$ min, $t=-2.54$ $p=0.011$). Weekends were not a relevant factor for sleep duration (Table S2). Counterintuitively, this loss of sleep did not correlate with an increase in daytime siestas; on the contrary, our data suggests a decrease in napping across time. According to sleep logs, the proportion of participants that reported naps decreased from 75% in 2012 to 36% in 2024, as did the weekly frequency of naps (Fig. S2.A).

The start of sleep displayed a sharp delay of over an hour in both Toba/Qom communities, with a slightly larger delay in the summer (Fig. 3.A, Table S3). The rural group delayed its time of sleep start by 75±8 minutes (from 22:55 in 2013 to 00:10 in 2023; $t=8.88$, $p<0.001$) and 87±7 minutes (from 23:10 to 00:33; $t=12.60$, $p<0.001$) in the winter and the summer, respectively; while the delay in the urban group was 74±11 minutes (from 22:51 to 00:05; $t=6.66$, $p<0.001$) and 91±8 minutes (from 23:01 to 00:31; $t=11.39$, $p<0.001$), respectively.

The wake-up time also displayed a differential evolution according to season (Fig. 3.B, Table S3). We detected a large delay in the urban community in both seasons (Winter: from 7:15 in 2013 to 8:09 in 2023, $\Delta= 61\pm11$ min, $t=5.09$, $p<0.001$; Summer: from 6:41 to 7:57, $\Delta= 76\pm8$ min, $t=9.80$, $p<0.001$). The rural Toba/Qom group showed a lesser delay only in the long photoperiod season (from 7:29 in 2013 to 8:03 in 2023; $\Delta= 34\pm7$, $t=4.93$, $p<0.001$), while there was no relevant change in the short photoperiod season (8:13 to 8:24).

The midpoint of sleep evolved predictably based on the changes in sleep onset and offset described above (Tables S2 and S3). The fixed factor "free-day/workday" revealed a very small, albeit statistically significant, effect on the midpoint of sleep, indicating that social jet-lag is hardly relevant in these communities (midpoint of sleep is 11 min [95% CI: 8-13 min] later on nights preceding a free day, $t=7.99$, $p<0.001$).

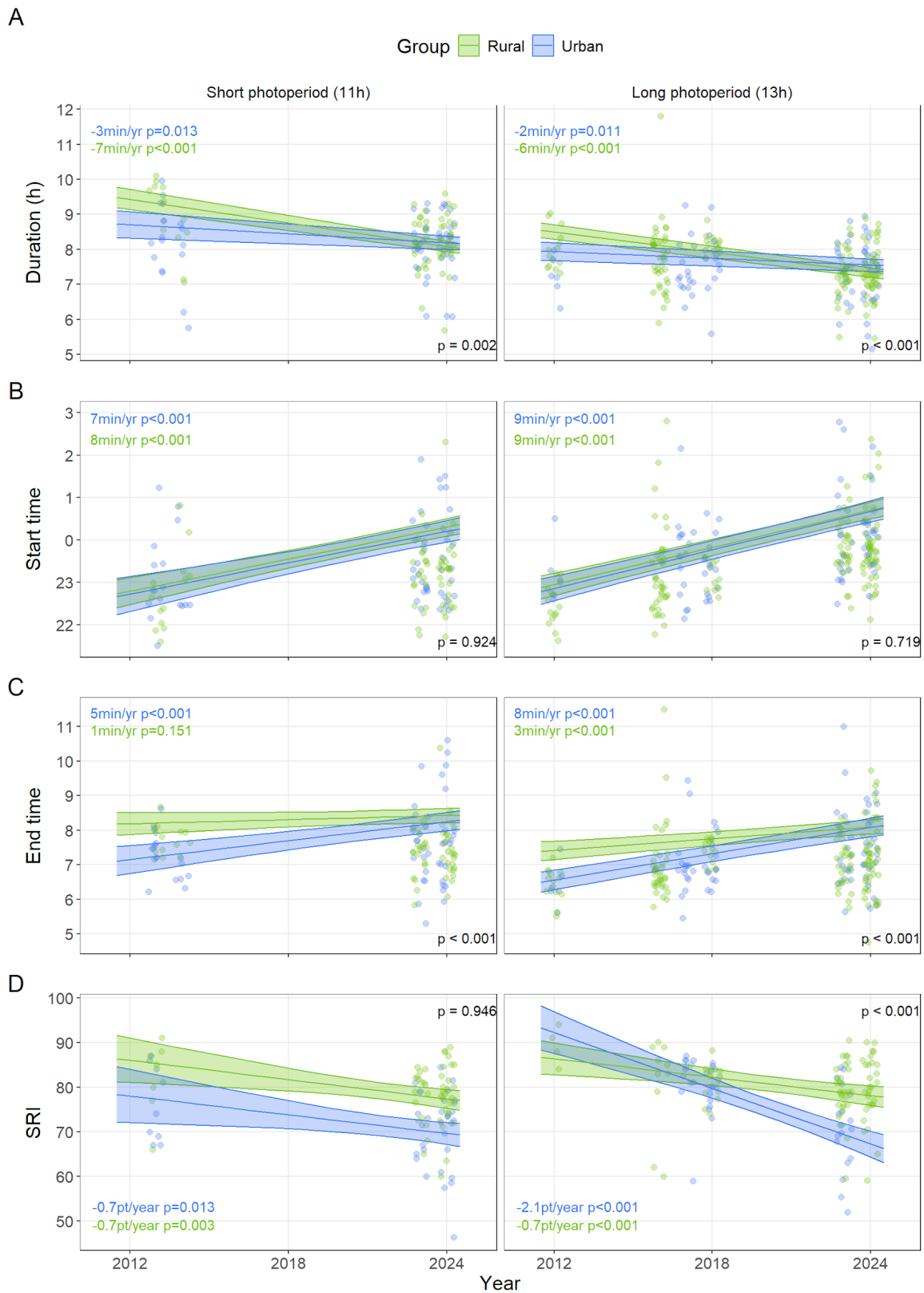

Fig. 3. Evolution of different sleep variables in Toba/Qom communities from 2012 to 2024. **(A)** Sleep duration (in hours), **(B)** sleep start time, **(C)** sleep end time (both in clock time), and **(D)** sleep regularity (measured by the Sleep Regularity Index). Individual points represent the average of actual data for all participants in each study since 2012 within the photoperiod length

windows 10.5 to 11.4h (Winter) and 12.5 to 13.4 (Summer); all data recorded outside of these photoperiod windows are included in the models but are not plotted here. Light color bands represent the average ± SE prediction of the LMEMs for a 22 y.o. participant in each community at each season across time (averaged for sex and workday/free day). Color labels indicate the slope values (in units/year) for each group, and the corresponding p values. The black labels display p values for the contrast of slopes in each panel. All p values were Tukey-corrected for multiple comparisons.

We measured the regularity of nightly sleep using two complementary metrics, allowing us to better assess potential sleep disruption in these communities (*15*). The Sleep Regularity Index proposed by Philips et al.(*16*) captures sleep regularity over consecutive events, while the standard deviation of the onset of sleep provides an overall estimation of the regularity of bedtime habits, regardless of consecutiveness.

SRI was calculated for any series of not less than 7 consecutive nights of recording. Both communities displayed a reduction in SRI across time (Fig. 3.D, Table S3). The most significant reduction was observed for the urban group in the summer season, with a drastic decrease of 20.9±2.7 points, from 90.1 in 2013 to 69.3 in 2023 ($t=-7.72$, $p<0.001$); in the winter, the reduction was milder at 7.0±2.8 points (from 77.3 to 70.3, $t=-2.50$, $p=0.013$). The rural community showed a decrease in the SRI of about 7±2 points in both seasons (from 85.3 in 2013 to 78.1 in 2023 in the winter, $t=-3.01$, $p<0.001$; and from 85.7 to 78.7 in the summer, $t=-3.58$, $p<0.001$).

We then analyzed the changes in the standard deviation of sleep onset times within each individual using a generalized linear mixed-effects model (Table S2). Irregularity in the start of sleep was slightly higher in the urban group (estimate = 0.16 SDs [95% CI: 0.03-0.28], $t=2.52$, $p=0.012$), and in the winter season (estimate = 0.12 SDs [95% CI: 0.02-0.22] more than in the summer, $t=2.20$, $p=0.029$). Our model predicts that sleep onset irregularity increased similarly in both communities, about 0.40 SDs [95% CI: 0.30-0.50] in the 2013 to 2023 decade ($t=6.66$, $p=0.029$). In summary, our results on SRI and sleep onset variability indicate that sleep became more disrupted in these 10 years.

Discussion

Our analysis reveals the impact of the introduction of electricity on sleep timing in a preindustrial community in real-time. Based on twelve thousand recorded sleep events across twelve years, our models reveal drastic changes in sleep timing, including a delay in sleep onset of more than 1.5 hours and a reduction in daily sleep duration of more than one hour that correlate with the introduction of electricity in rural communities, and the potential of increased exposure to nocturnal light. Our results mimic —in a timespan an order of magnitude shorter— what was likely a century-long historical change in sleep phase and duration as humans transitioned from preindustrial to industrial and postindustrial environments (*17*). However, our finding that urban communities who already had access to electricity at the start of our field studies also displayed a delay in the time of sleep and a shortening of sleep duration suggests that there are other factors correlated with the availability of electricity that go beyond the use of electric light, such as smartphones, TV sets, and the internet. In this sense, our results highlight both the powerful effects of electric light, as well as the access to other devices and features that are now standard in modern industrial societies, on human behavior. Our study also underscores the fundamental importance of monitoring the impact of the introduction of modern technologies on the lifestyle and well-being of preindustrial communities.

Our two Toba/Qom groups represent a good example of how living environments can differentially modulate the effects of the introduction of electricity and other features on sleep. While we detected similar delays in the time of sleep onset, only the urban community displayed a comparable delay in the offset of sleep, while the rural group displayed no change in the winter and a smaller delay in the summer. These differences largely explain the drastic reduction in sleep duration in the rural group. These rural communities, who live under even more limited and exposed conditions than their counterparts in the city of Ingeniero Juárez, may not be able to extend their sleep much later in the morning either due to natural causes (sunlight, temperature), to the need to commence with sustenance activities (e.g. harvesting firewood, managing livestock, gathering), or to other necessities related to their isolated rural environments (e.g. distance to health centers or convenience shops, lack of transportation options).

In postindustrial settings, it has been found that people have a delayed sleep phase, and in some cases, sleep less in the winter than in the summer (reviewed in (*18*)). One study found that the delayed sleep phase was predicted by each individual's low exposure to natural light and high exposure to electric light in the evening during the short photoperiod season (*18*). Previous work with Toba/Qom communities showed that access to electricity correlates with a delay in the circadian clock —determined through the onset of melatonin release— only in the winter, when electric light becomes more relevant to extend active hours (*19*). It remains to be determined whether the drastic delays in sleep onset, both during the winter and summer, after the arrival of electricity to the rural community are associated with a delay in the circadian biological clock.

Internet access and devices such as smartphones, however limited in supply, have allowed Toba/Qom communities to connect to a world beyond their local environment, mostly through social media and video platforms. The adoption of these technologies has been very rapid. To the best of our knowledge, smartphones were virtually nonexistent by 2018, yet by 2024 half of Toba/Qom participants owned a smartphone (and most who did not reported they would often borrow one from a family member), and about the same had access to a TV, or a computer in their homes, reflecting a swift shift toward digital connectivity. A public internet antenna was installed as recently as 2022 in Isla García, providing free internet access to the community; one family in Vaca Perdida even had a satellite internet connection. These technological advances likely favor the delay of sleep and, whenever the time for waking up cannot be further delayed, the reduction of sleeping time in two ways: on the one hand, it provides almost unlimited entertainment for the night hours, but on the other, it opens a door into the "modern" lifestyle, of which nightlife is a central element. This is particularly more relevant in Argentina, where, for instance, the TV "prime time" extends from 21:00 to midnight and soccer matches can start as late as 22:00 (*20*). This phenomenon merits further research incorporating Toba/Qom self-perceived experiences regarding access to electricity and electric light sources, as well as the roles of the internet, the TV, and other electronic devices.

Sleep loss is considered a modern world epidemic with significant consequences for public health, performance and safety, learning and memory, and overall economic impact (*21–24*). Lack of sleep can affect health at several levels, including, but not limited to, cardiovascular, metabolic, immune, and mental health (*25*, *26*), and is a strong predictor of all-cause mortality (*27*). Since we started studying their sleep patterns in 2012, our model indicates that rural Toba/Qom communities have lost a whole hour of sleep —a change that would be hard to imagine not affecting this community's health. Although even in the worst scenario in our model (i.e. the summer) the predicted average sleep duration is still within the consensus recommended sleep duration range (*28*), we need to note that these recommendations are aimed at people in modern developed societies. For a deeply underprivileged population such as the Toba/Qom, which experiences reduced access to health services and clean water supply, dwells in an extremely harsh rural environment, and suffers from malnutrition (*29*), such a sharp reduction of

sleep time is likely more challenging for health and wellbeing than in developed postindustrial settings.

The observed reduction in sleep regularity in both communities is also concerning. Sleep regularity has gained attention recently as a marker of sleep health (*15*), and has been proposed as a more precise predictor of the negative impacts of poor sleep than sleep duration itself (*30*). Delayed sleep has already been associated with low sleep regularity in hyper-industrialized societies (*16*), and in a study combining data from adolescents in the Toba/Qom and in rural communities of Southern Brazil, we already reported that sleep regularity was reduced in students exposed to electric light in the evening hours (*31*). The current study reveals that sleep regularity, measured both by the Sleep Regularity Index and by the standard deviation of sleep onset, has diminished significantly in both rural and urban Toba/Qom communities in the last decade. Further investigation should determine whether this change is driven by the mere access to electric light and other electric appliances and devices at home, and/or if it is correlated with habit modifications involving the whole community.

Numerous studies of preindustrial communities support the notion that electricity and other postindustrial environmental factors impact sleep timing (*4*). However, the hypothesis that industrialization has necessarily shortened sleep remains under debate. A recent meta-analysis, for instance, suggests that people in industrialized societies sleep longer than those in preindustrial settings, and attributes modern sleep-related health issues not to shorter sleep but to heightened circadian disruption (*3*). However insightful, these observations need to be carefully weighed, considering the inherent diversity of pre-industrial and industrialized groups, without overlooking the unique environmental and sociocultural factors that can shape sleep. Our longitudinal study of the Toba/Qom communities provides a rare opportunity to observe the real-time impact of modernization, including the acquisition of electricity and related technologies. Our data reveals that the modernization of Toba/Qom communities correlates with a drastic reduction in sleep duration and an increased circadian disruption —marked by a reduced sleep regularity and the further decoupling of sleep onset from sunset. We should also note that the transition from harsh preindustrial conditions to an electrically lit postindustrial environment can also have beneficial effects on sleep, for example, by improving comfort and sense of safety at bedtime (*32*). This underscores the intricate ways in which the environment and modernization interact to shape human sleep patterns (*33*).

Some limitations in our study need to be addressed. First, it should be noted that the recordings in our dataset have been obtained using different devices and algorithms. Because of the long timespan of our study, this was an obstacle hard to overcome. Of note, the Actiwatch devices used from 2012 to 2018 do not provide raw accelerometric data, as the Axivity AX3 devices do, precluding us from using a common algorithm to extract sleep timing. However, we trust that the different methods are sufficiently comparable as they are all based on longitudinal wrist-accelerometry and the sleep estimation was performed following well-tested protocols, based on similar criteria of activity/inactivity, aided by sleep logs to detect unreliable estimations. Moreover, our tests indicate that sleep estimation from AX3 and Actiwatch Spectrum devices are comparable (see Fig. S3), especially considering the large amount of data available. Given the magnitude of the effects estimated by our statistical models, it is improbable that slight differences in the measuring tool would artificially generate the changes we observed.

Second, thanks to the improvement of fieldwork conditions, in terms of the available equipment and our relationship with the communities, our dataset is much denser in recent years, compared to the first four years of work. While this may pose a limitation in the model's precision for those early years, the use of linear models, including random effects accounting for sex, age, and repeated measures, is robust enough to assess the dynamics of sleep across the studied period in these communities.

Our work highlights the challenges and multifaceted impacts of technological innovation on human behavior and health, especially among underprivileged populations. While these communities have finally received the innumerable benefits of access to electricity, smartphones, and the internet, they remain significantly behind in accessing many of the advantages of modern, developed societies. This disparity may exacerbate the negative consequences of delayed and shortened sleep in these communities, which seem to be inescapable features of modern lifestyle. In this sense, the Toba/Qom case we present exemplifies what has been described as *"cultural arrhythmia,"* i.e., an imbalance between the pace of changes in human lives and their surrounding habitats (*34*) (p.63). In this sense, it is imperative that such transformative processes consider the unique features and conditions of each community, ensuring they enhance health and overall well-being while proactively addressing any potential challenges.

In summary, here we present a real-time glance at a unique scenario to study the changes in human sleep patterns through the introduction of electricity, nighttime light exposure, and the incorporation of specific technologies. These findings offer one of the clearest demonstrations to date of the direct consequences of electric light on nightly sleep in humans at both the individual and population levels. These results also highlight the urgent need to design specific public health policies and awareness campaigns to protect sleep health in groups that might be particularly vulnerable to these changes.

Methods

Ethics

All the activities described in this work, past and recent, were reviewed and approved by the Internal Review Board from the University of Washington's Human Subject Division and followed the Declaration of Helsinki. The research did not involve any risk to participants or researchers.

Experimental design and participants

The participants belonged to three Toba/Qom communities in Formosa, a northern province in Argentina, all of which share a recent historical past and are closely related culturally and ethnically (*8*):

1) *Barrio Toba*: a community located adjacent to Ingeniero Juárez (23°47′ S, 61°48′ W), a town with close to 20,000 inhabitants including the Toba/Qom people. This community has had 24/7 access to electricity at their homes throughout the time we surveyed them. People in this community settled adjacent to Ingeniero Juárez after migrating from the northern Toba/Qom communities in the 1990s.
2) *Vaca Perdida*: a rural community of a few hundred members located ~60 km north of Ingeniero Juárez (23°29′ S, 61°38′ W). This community slowly gained access to electricity when the local government started introducing it in 2016 and has since had regular access to electricity and, more recently, paid internet access.
3) *Isla García*: this small rural community (50-70 people) is named after the family that founded it. Since we started working with them, the García family and their relatives have moved through three different locations in the vicinity of Vaca Perdida. The first year they were able to consistently access electricity was 2017, and since 2018, they have remained at their current location with full access to electricity. In 2023, the local government installed a public internet antenna on the community grounds.

Consent was obtained orally from every participant after detailing the study procedures in Spanish, with the help of a Toba/Qom translator whenever necessary. For subjects under 18 years of age, consent as well as assent by one of the parents were obtained. Participants were not monetarily compensated for their participation in any of these studies. In appreciation of their participation, they received different gifts, usually clothing and daily use items.

It is important to note that these communities engage in very similar social behavior and cultural activities. Children and adolescents attend school during daylight hours, although the time for each age group may differ slightly between communities. Schools are typically located within walking distance of the houses. Most adults are formally unemployed and rely economically on occasional gigs and government assistance. Of note, substance abuse disorders are rare among these communities, in part due to their Anglican religious practices; indeed, selling alcohol is forbidden in Vaca Perdida.

Classifying rural and urban communities includes considering factors such as access to electricity, built housing, and market and labor integration. Beyond their history of access to electricity, rural communities are far from health, continued education, and administrative centers, grocery shops, and banks, and usually lack transportation mediums of their own to travel the challenging ~60 km road necessary to access these in Ingeniero Juárez. The "rural" group in this paper is represented by the aggregated data of both Vaca Perdida and Isla García participants. The Toba/Qom community in Barrio Toba will be assigned the "urban" label in this paper, due to being settled within an urbanized area, even if their access to these urban amenities maybe limited due to their economic situation.

Data acquisition, treatment, and analysis

Data was collected at different points between 2012 and 2014, 2016 and 2018, and 2023 and 2024, and comprises a total of 12,307 recorded sleep events from 156 participants. Data was recorded mostly in the late fall or early winter, and in the late spring or early summer, to better capture seasonal differences. Table S1 details the number of participants, their age and sex composition, and the number of recorded events according to community, year, and season of collection. One-hundred and fifty-six (156) unique subjects participated in the study (94 from the rural group, 63 from the urban group; one participant moved from the urban group to the rural group after 2018; 52% females). Table S4 indicates the total number of participants in each field campaign, split by study group, along with the number of participants recorded for the first time in each. Table S5 shows the distribution of records across participants, in terms of the number of campaigns in which they participated; around 50% of the participants were recorded at two or more timepoints. Fig. 1.B further illustrates the longitudinal nature of our study.

All the data manipulation and analysis were carried out in the *R* language (*35*) (version 4.4.2) on the RStudio platform (*36*) unless specifically indicated.

Sunlight data

Solar data for the Ingeniero Juárez and Vaca Perdida geographical regions was obtained using the *suncalc* package (*37*). For every date present in the dataset, we collected the sunrise and sunset times. These were used to calculate the natural photoperiod for each date, as well as for the filtering of nightly sleep episodes that are described below.

Longitudinal study of light pollution

Longitudinal values of night light pollution were obtained by the Day/Night Band of NASA's Black Marble Group's Visible Infrared Imaging Radiometer Suite instrument (VIIRS DNB, zero point corrected). Square one km^2 areas surrounding the location of the studied communities were

selected using the Radiance Light Trends application (https://lighttrends.lightpollutionmap.info/), and values were downloaded for all months from April 2012 to July 2024. Satellite images of the regions of interest superimposed with VIIRS radiance data through the years were obtained from Jurij Stare's Light Pollution Map (www.lightpollutionmap.info).

Locomotor activity and sleep estimation

Sleep was assessed by wrist actigraphy, and participants also completed daily sleep logs throughout each recording session. Participants wore the actigraphs on their non-dominant wrists, and locomotor activity data was always collected in one-minute bins. Individual recordings were visually examined before proceeding to the sleep estimation to confirm data integrity and discard low-quality recordings (e.g. fragmented data, frequent missing periods of data, frequent saturated counts of activity).

Three different wrist-actigraphic devices were used across the years, and consequently, the methods used for sleep detection also differed:

1) Participants in the studies before 2014 wore the Actiwatch-L device from Mini Mitter (Bend, OR); data was analyzed for sleep detection, aided by sleep logs, using the Sleep Analysis package of the Mini Mitter Software (version 3.4), as described in (*9*).
2) Participants recorded between 2014 and 2018 were equipped with the Actiwatch Spectrum Plus loggers from Respironics (Bend, OR); sleep detection was performed using the Philips Respironics Actiware software V.6.0.9, as described in (*38*).
3) The newly reported data in this paper collected since 2023 was obtained with the AX3 devices from Axivity (Newcastle upon Tyne, UK), which are equipped with a tri-axial accelerometer. Devices were set at 50hz with a range of 8g. Sleep detection was performed using the GGIR software for R (*39*) using the implemented Van Hees algorithm (*40*).

Algorithm-based sleep detection from data cohorts 2 and 3 above was contrasted with individual sleep logs non-exhaustively to assess the overall rationality of estimations.

We are aware that the use of different devices and algorithms imposes an important limitation on the precision of our analysis. However, we have strong reasons to trust our overall conclusions: firstly, daily sleep logs were used to check the reliability of the detected sleep bouts, and secondly, all three combinations of devices and algorithms estimate sleep based on criteria of sustained activity/inactivity on one-minute bins of actigraphic recordings.

Moreover, we performed a comparison of the sleep/wake estimations of the Actiwatch Spectrum Plus and the AX3 devices by comparing the data obtained from 22 non-Toba/Qom volunteers using both devices on their non-dominant wrist concomitantly for 7 to 14 days. We performed a Bland-Altman analysis based on 206 hundred sleep events, selected with the same criteria used for the Toba/Qom data (described in the next subsection). Due to the non-normality of the differences, we performed a non-parametric analysis of the results (following the recommendations by Bland & Altman 1999 (*41*)). The analysis revealed that differences between the AX3/GGIR and Actiwatch/Actiware methods can take a wide range of values, but that the median of these differences is very small for both sleep start and end time, as well as for duration. Differences between methods, expressed as AX3/GGIR minus Actiwatch/Actiware: for sleep start, mean = 16.5 min, median = 1.4 min; for sleep end, mean = -0.9 min, median = 2.6 min; for sleep duration, mean = -17.5 min, median = 1.2 min. See Fig. S3 for more details. All of these suggest that these two methods should provide very similar estimates for a large enough sample such as ours, comprising over ten thousand data points. Moreover, the observed mean differences between methods are much smaller than the observed effect sizes.

Sleep data treatment and cleaning

The whole 2012-2024 dataset of sleep events was filtered first to keep only nightly sleep events. Every sleep event starting outside the hours from dusk till dawn on any date was removed from the dataset. This step removed only 181 sleep events (1.5% of the total sleep events). While actigraphy performs poorly for the detection of naps, daytime sleep is rare in these Toba/Qom communities. According to the analysis of sleep logs, the proportion of Toba/Qom that reported naps decreased from 75% in 2012 to 36% in 2024 (Fig. S2.A). The frequency of reported siestas was very low and changed only slightly, from a median of 2.3 naps per week in 2012 to only one nap per week in 2024 (Fig. S2.B).

We then proceeded to detect events that could be considered outliers based on their duration (i.e. too long or too short events). This approach allowed us to remove data points that could represent either artifacts of the sleep detection method, or sleep events from "non-representative" nights (e.g. during travel, transiting sickness). The outlier analysis was performed using the median absolute deviation (MAD) method (*42*) from the *Routliers* package (*43*), using a threshold of 2.5 MADs (lower limit = 3.48h, upper limit = 12.44h). This step removed an additional 506 (4.1%) sleep events from the dataset. The final dataset on which the analysis was performed had a size of 11,620 sleep records.

Sleep regularity

Sleep regularity was evaluated by combining two metrics, one "consecutive metric" and one "overall metric", following the recommendations of Fischer et al. 2021 (*15*): the Sleep Regularity Index (SRI) and the standard deviation of sleep onset times, respectively.

The SRI, proposed by Phillips et al. 2017 (*16*), represents a re-scaled measure of the probability that a participant is at an equal state of wake or sleep at two time points separated by 24 hours on any series of at least seven consecutive night sleep events. A person who always wakes up and falls asleep at the same time every day will score 100, while a person who randomly falls asleep and wakes up at any time of the day will score 0. Only scores for sets of at least seven consecutive recordings were included in the analysis. It is important to note that for the SRI analysis, the filter step of outliers based on sleep duration described above was purposefully not performed, as we preferred to prevent the loss of the continuity of recordings even if that meant including potentially conflicting sleep events.

Then, the standard deviation of the time of the start of nightly sleep was calculated for each participant with at least seven recorded sleep events (consecutive or not) at any given field campaign.

Statistical analysis

To evaluate the evolution of night sleep timing in these communities, we used linear models including mixed-effects (LMEMs) with the *lme4* package (*44*). Fixed factors included a binary rural/urban factor, calendar year, photoperiod length, type of day (before a workday or before the weekend or a holiday), sex, and age. Individual identities were included as a random factor to account for repeated measures. Statistical significance was tested through a Type III ANOVA as implemented in the *parameters* package (*45*).
Exclusively for the analysis of the sleep start, midpoint, and end variables, the age factor was included as a 3-grade polynomic term to account for the known non-linear progression of sleep timing across adolescence and adulthood (*46*). Below is an example of a *lme4* LMEM equation in this study, illustrating the interaction terms and general syntax:

*Sleep_onset ~ Group * Year * Photoperiod_length + Sex * poly(Age, 3) + Week_day + (1|participant_ID)*

For the analysis of sleep regularity variables, the syntax was almost identical to the model described earlier, except for the exclusion of the variable of the type of day, as it does not apply to values summarized over several nights. For the analysis of the standard deviations in sleep onset times, it is appropriate to use a generalized linear mixed-effects model (GLMEM), also using the *lme4* package. This specific analysis also requires recentering all factors and using a gamma distribution on a logarithmic scale.

The assumptions of the models were evaluated using the *check_model* function from the *performance* package (*47*). We tested the following features: 1) *posterior predictive check* (are real values far from modelled values?), 2) *linearity*, 3) *homogeneity of variance*, 4) *normality of residuals*, 5) *normality of random effects*, and 6) *influential observations* (are there too many outliers?).

To evaluate post-hoc contrasts between years or groups, we used the *emmeans* package (*48*). The tools in this package return the values of the dependent variable predicted by the LMEM/GLMEM based on given independent variables values, and test contrasts between levels (p-values are Tukey-corrected for multiple comparisons). When a classification of photoperiod length was required, we selected the values of 11h and 13h, which are round representative values of the seasonality in this geographical area. A ten-year span between 2013 and 2023 was used when comparing between years to allow for an easier appreciation of the magnitude of the results. Because we were not interested in analyzing sex differences, this variable was not fixed in contrasts and thus the returned predictions represent an average value between sexes. We decided to set the modelled age at 22 years old, which is the median age of participants in the dataset across all recording campaigns. It is important to note that age was not included as an interacting factor with groups, years, or photoperiod length in our models, and thus while the absolute predicted values can change according to their dynamics through age, the differences in the contrasts between the aforementioned factors do not change regardless of the set age value. In other words, had we applied our model to a 40-year-old participant, the delays or advances in sleep timing between the two communities would be the same, even when absolute sleep times may be different.

Survey of electronic devices access

Starting in the 2023 Spring campaign, when signing up, each participant was asked whether they owned a smartphone; those who did not were asked whether they would borrow one daily. After the last campaign in 2024, we followed-up by asking participants if they had access to a TV, a computer or tablet device, and/or an internet connection at their homes (of note, some participants declared having internet available to them even if they did not have a device to connect to it, due to having access to a public free internet connection).

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Data collection: LPC, IS, LLT, MFC, CRGP, VYZ, HOD

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Writing—original draft: LPC

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Data and materials availability: sleep data will be made available in a public database; link provided upon publication of the manuscript.

Supplementary Materials

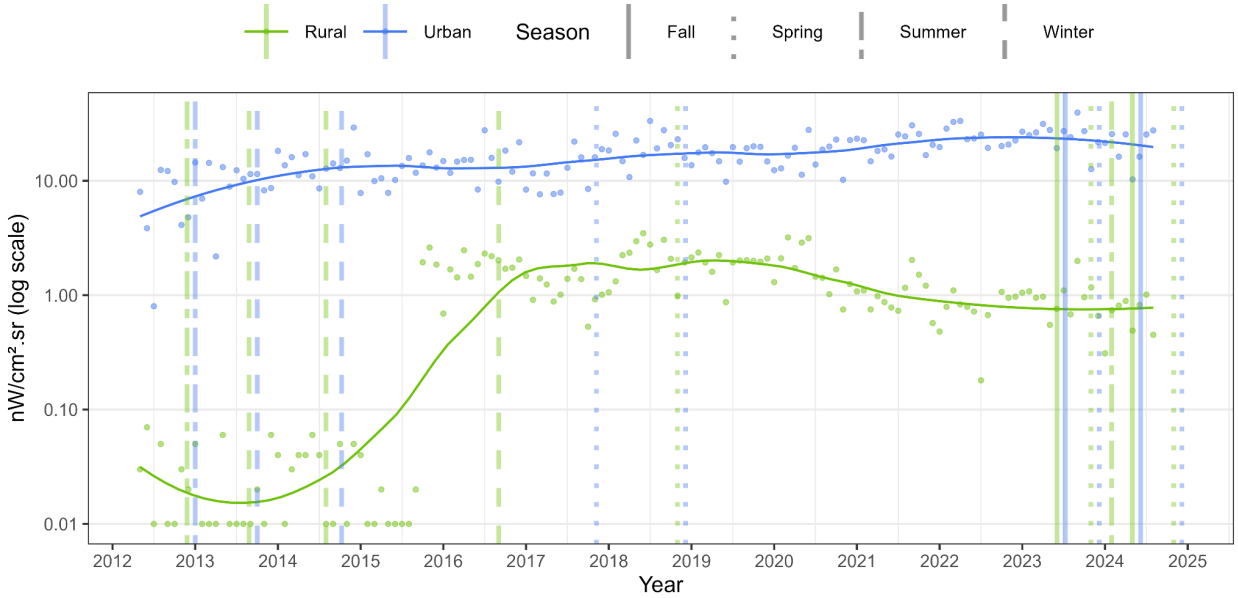

Fig. S1. **Evolution of night light pollution in the study areas.** Monthly night radiance values (log scale) for 1 km² areas around Barrio Toba in Ingeniero Juárez (urban) and the centre of Vaca Perdida (rural). The sharp increase in 2016 marks the beginning of work to install the electricity grid in the rural area. Vertical lines indicate approximate times of data collection since 2012; lines were purposefully spaced during field campaigns that included both groups for easier visualization. Line types indicate the season when data collection started.

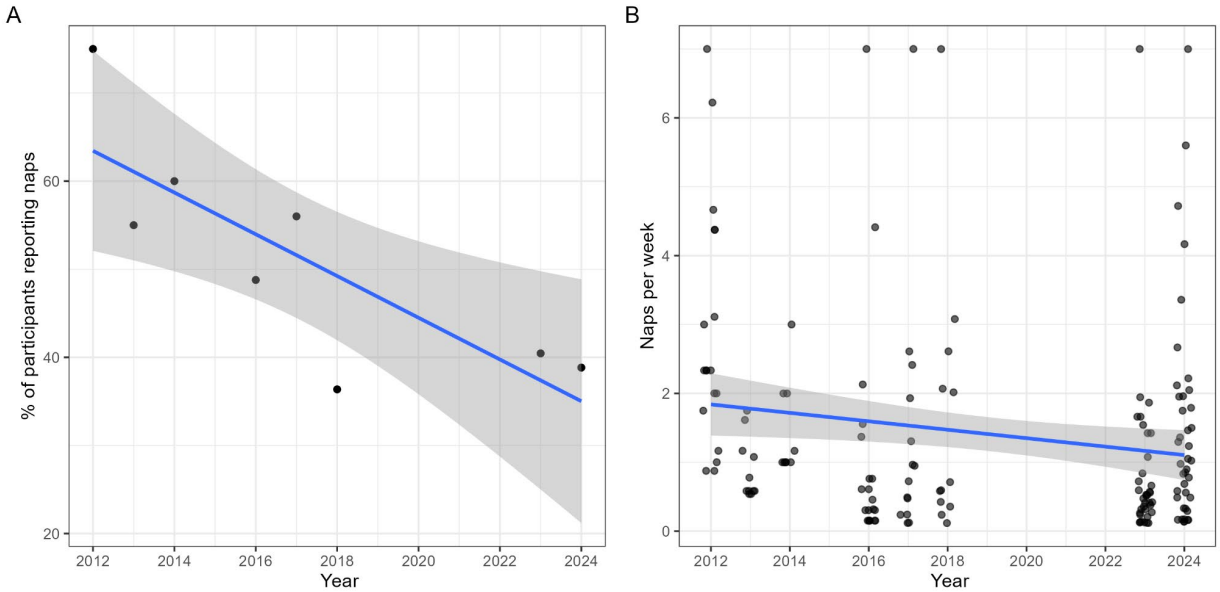

Fig. S2. **Evolution of naps in the Toba/Qom communities studied. (A)** Percentage of participants that reported at least one daytime nap during a recording period, split by year. **(B)** Frequency of daytime naps reported (in naps per week), by year. Lines and shades represent linear regressions of the datapoint, with added standard errors.

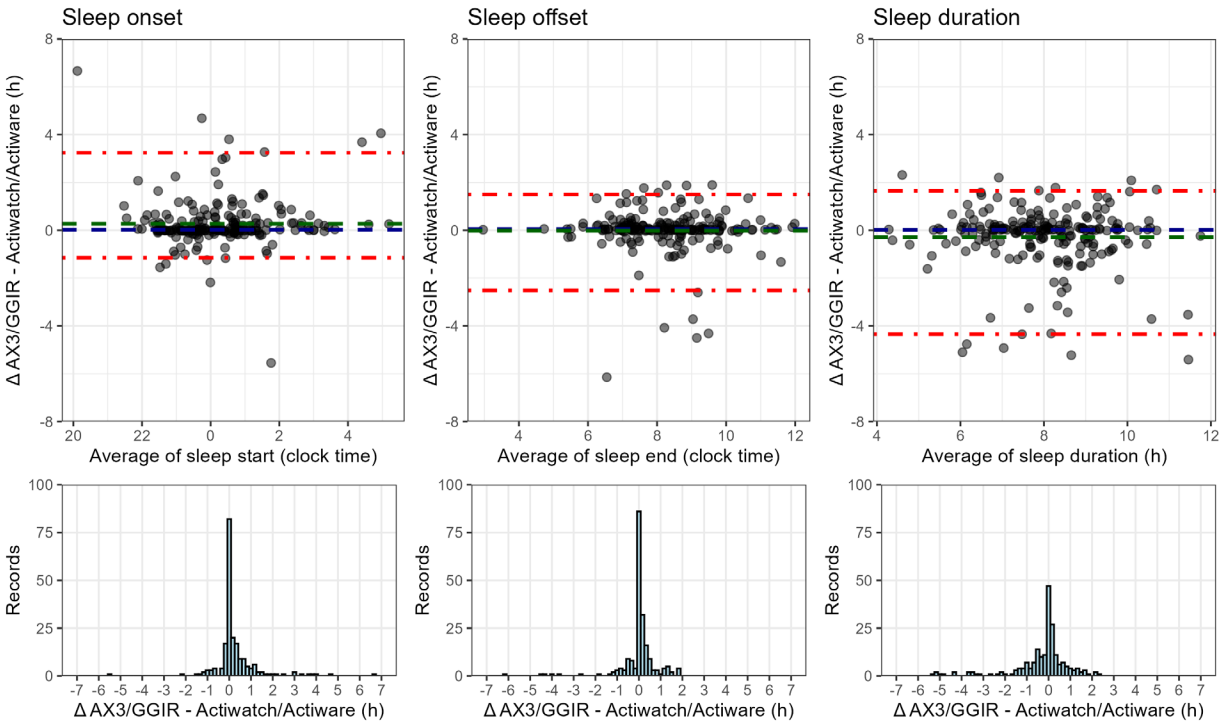

Fig. S3. Comparison of the Axivity AX3+GGIR and Actiware Spectrum Plus+Actiware methods for the detection of sleep from wrist-actigraphy recordings. Data consists of 206 detected sleep events (subject to the same cleaning procedure as the data from the main study) from 22 subjects wearing both devices on their non-dominant wrist from 7 to 14 days. Top: Bland-Altman analysis of the differences. The red dashed lines indicate the margin containing 95% of the observations; the blue dashed lines represent the mean of the differences, while the blue dashed line represents the median. Bottom: Distribution of the observed differences.

Year	Community	Dates	Participants	Recording events	% Female	Median age	Mean age	Minimum age	Maximum age	Data origin
2012	IJ	Nov	6	32	50	21.8	29.3	18	49.2	(9)
2012	VP	Nov- Dec	8	67	50	28.9	33.5	14.7	59.7	
2012	IG	Nov - Dec	6	39	50	16.1	17.8	14	29.9	
2013	IJ	Aug	11	154	72.7	29.7	29.7	17	46.3	
2013	IG	Aug	8	120	50	27.9	26.4	14.7	36	
2014	IJ	Aug	6	31	50	30.7	36	28.8	47.3	unpublished (*)
2014	IG	Jul - Aug	5	37	60	17.6	24.5	15.7	37	
2016	VP	Aug - Oct	18	605	44.4	24.5	25.3	12.3	57.2	(38)
2016	IG	Aug - Oct	25	1124	60	18	23.2	12.2	51	
2017	IJ	Sep - Nov	17	736	58.8	25.4	28.1	12.3	75.2	
2018	IJ	Oct - Dec	15	723	66.7	21.1	25.3	14.8	42.3	
2018	IG	Oct - Dec	11	517	54.5	16.9	17.4	13.5	21.8	
2023	IJ	May - Jun	19	390	73.7	22.6	23.8	13.6	45.5	unpublished
2023	VP	May - Jun	9	367	88.9	17.7	20.8	12.3	37.5	
2023	IG	May - Jun	11	440	45.5	21.4	26.5	14.1	45.8	
2023	IJ	Oct - Dec	19	937	68.4	23.4	25.2	14	47.3	
2023	VP	Oct - Dec	15	678	80	20.1	24.4	12.7	45.3	
2023	IG	Oct - Dec	14	504	57.1	21.6	24	14.5	41.8	
2024	VP	Jan - Feb	15	357	80	20.4	24.7	13	45.6	
2024	IG	Jan - Feb	14	367	64.3	21.2	22.6	14.8	42.1	
2024	IJ	Apr - Jun	20	947	60	24.3	27.1	14.6	47.8	
2024	VP	Apr - Jun	26	1065	69.2	19.4	22.5	13.1	45.9	
2024	IJ	Oct - Nov	22	684	45.5	24.2	26.8	12.8	48.3	
2024	VP	Oct - Nov	28	1091	60.7	19.8	22.8	13.5	46.3	
2024	IG	Oct - Nov	13	295	38.5	18.6	17.9	12.3	22.9	

Table S1. Number of participants and demographic data from all field campaigns included in the dataset.
IJ: Ingeniero Juárez; VP: Vaca Perdida; IG: Isla García.
(*) Participants were part of the dim-light melatonin onset study in Casiraghi et al., 2020 (19).

Variable	Parameter	Coefficient	SE	95% CI	t	p
Sleep duration (h)	*Intercept*	17.85	2.16	13.62 to 22.09	8.263	<0.001
	group: Urban (vs. Rural)	-2.80	3.54	-9.75 to 4.14	-0.792	0.429
	calendar year (per year)	-0.20	0.10	-0.39 to -0.01	-2.113	0.035
	photoperiod length (per hour)	-0.56	0.17	-0.91 to -0.22	-3.228	0.001
	type of day: Workday (vs. Weekend)	0.00	0.03	-0.06 to 0.07	0.041	0.968
	sex: Male (vs. Female)	0.05	0.20	-0.35 to 0.44	0.236	0.813
	age (per year of age)	-0.04	0.01	-0.05 to -0.03	-6.378	<0.001
	group x calendar year: Urban	0.10	0.16	-0.21 to 0.4	0.626	0.531
	group x photoperiod lenght: Urban	0.11	0.29	-0.44 to 0.67	0.402	0.688
	calendar year x photoperiod lenght	0.01	0.01	-0.01 to 0.02	1.058	0.290
	sex x age: Male	0.00	0.01	-0.02 to 0.01	-0.553	0.580
	group x year x photoperiod: Urban	0.00	0.01	-0.03 to 0.02	-0.209	0.835
Sleep onset (h)	*Intercept (*)*	21.05	2.04	17.06 to 25.05	10.326	<0.001
	group: Urban (vs. Rural)	0.60	3.44	-6.14 to 7.33	0.174	0.862
	calendar year (per year)	0.01	0.09	-0.16 to 0.19	0.160	0.873
	photoperiod length (per hour)	-0.04	0.16	-0.36 to 0.28	-0.260	0.795
	type of day: Workday (vs. Weekend)	-0.18	0.03	-0.24 to -0.12	-6.238	<0.001
	sex: Male (vs. Female)	0.69	0.14	0.42 to 0.96	4.995	<0.001
	age 1st-poly degree (per year of age)	16.05	9.19	-1.95 to 34.06	1.747	0.081
	age 2nd-poly degree (per year of age^2)	14.72	10.86	-6.57 to 36.01	1.355	0.175
	age 3rd-poly degree (per year of age^3)	67.71	9.94	48.22 to 87.2	6.810	<0.001
	group x calendar year: Urban	-0.04	0.15	-0.34 to 0.25	-0.295	0.768
	group x photoperiod lenght: Urban	-0.06	0.27	-0.6 to 0.48	-0.212	0.832
	calendar year x photoperiod lenght	0.01	0.01	0 to 0.02	1.406	0.160
	sex x age^1>: Male	21.77	11.67	-1.1 to 44.64	1.866	0.062
	sex x age^2>: Male	-65.25	11.98	-88.73 to -41.78	-5.449	<0.001
	sex x age^3>: Male	-31.00	11.18	-52.91 to -9.09	-2.773	0.006
	group x year x photoperiod: Urban	0.00	0.01	-0.02 to 0.03	0.319	0.750
Sleep offset (h)	*Intercept (*)*	38.01	1.90	34.28 to 41.74	19.963	<0.001
	group: Urban (vs. Rural)	-3.02	3.24	-9.36 to 3.32	-0.933	0.351
	calendar year (per year)	-0.18	0.08	-0.35 to -0.02	-2.206	0.027
	photoperiod length (per hour)	-0.61	0.15	-0.91 to -0.31	-3.972	<0.001
	type of day: Workday (vs. Weekend)	-0.18	0.03	-0.23 to -0.13	-6.737	<0.001
	sex: Male (vs. Female)	0.56	0.15	0.26 to 0.85	3.727	<0.001
	age 1st-poly degree (per year of age)	-31.70	9.59	-50.5 to -12.9	-3.306	0.001
	age 2nd-poly degree (per year of age^2)	39.03	11.12	17.24 to 60.82	3.511	<0.001
	age 3rd-poly degree (per year of age^3)	61.48	9.96	41.94 to 81.01	6.170	<0.001
	group x calendar year: Urban	0.08	0.14	-0.2 to 0.36	0.572	0.567
	group x photoperiod lenght: Urban	0.10	0.26	-0.4 to 0.61	0.394	0.694
	calendar year x photoperiod lenght	0.02	0.01	0.01 to 0.03	2.758	0.006
	sex x age^1>: Male	29.01	11.95	5.58 to 52.44	2.427	0.015
	sex x age^2>: Male	-89.82	12.21	-113.74 to -65.89	-7.358	<0.001
	sex x age^3>: Male	-20.89	11.24	-42.93 to 1.15	-1.858	0.063
	group x year x photoperiod: Urban	0.00	0.01	-0.02 to 0.02	-0.074	0.941

Table S2. LMEM and GLMEM models' results for sleep variables.

Variable	Parameter	Coefficient	SE	95% CI	t	p
Sleep midpoint (h)	*Intercept (*)*	29.51	1.62	26.34 to 32.68	18.235	<0.001
	group: Urban (vs. Rural)	-2.21	2.76	-7.63 to 3.21	-0.800	0.424
	calendar year (per year)	-0.08	0.07	-0.22 to 0.06	-1.133	0.257
	photoperiod length (per hour)	-0.32	0.13	-0.58 to -0.07	-2.490	0.013
	type of day: Workday (vs. Weekend)	-0.18	0.02	-0.22 to -0.14	-7.994	<0.001
	sex: Male (vs. Female)	0.62	0.14	0.34 to 0.9	4.336	<0.001
	age 1st-poly degree (per year of age)	-10.28	8.86	-27.64 to 7.08	-1.161	0.246
	age 2nd-poly degree (per year of age^2)	32.68	10.10	12.88 to 52.48	3.236	0.001
	age 3rd-poly degree (per year of age^3)	69.81	8.93	52.31 to 87.3	7.820	<0.001
	group x calendar year: Urban	0.05	0.12	-0.18 to 0.29	0.449	0.653
	group x photoperiod length: Urban	0.09	0.22	-0.35 to 0.52	0.394	0.694
	calendar year x photoperiod length	0.01	0.01	0 to 0.03	2.491	0.013
	sex x age^1>: Male	29.04	10.83	7.81 to 50.26	2.682	0.007
	sex x age^2>: Male	-84.87	11.06	-106.55 to -63.19	-7.672	<0.001
	sex x age^3>: Male	-27.75	10.09	-47.54 to -7.96	-2.749	0.006
	group x year x photoperiod: Urban	0.00	0.01	-0.02 to 0.02	-0.122	0.903
SRI (units)	*Intercept*	97.6	42.9	13.3 to 181.9	2.275	0.023
	group: Urban (vs. Rural)	-178.2	67.2	-310.3 to -46.1	-2.652	0.008
	calendar year (per year)	-0.9	1.9	-4.6 to 2.9	-0.469	0.639
	photoperiod length (per hour)	0.0	3.5	-6.9 to 6.8	-0.004	0.997
	sex: Male (vs. Female)	-3.5	2.9	-9.2 to 2.2	-1.212	0.226
	age (per year of age)	0.0	0.1	-0.2 to 0.2	-0.144	0.886
	group x calendar year: Urban	7.8	3.0	1.9 to 13.7	2.599	0.010
	group x photoperiod length: Urban	15.4	5.5	4.6 to 26.3	2.807	0.005
	calendar year x photoperiod length	0.0	0.2	-0.3 to 0.3	0.100	0.920
	sex x age: Male	-0.1	0.1	-0.3 to 0.2	-0.584	0.560
	group x year x photoperiod: Urban	-0.7	0.2	-1.2 to -0.2	-2.862	0.004
SD of sleep onset (SDs)	*Intercept*	-0.04	0.05	-0.13 to 0.06	-0.765	0.444
	group: Urban (vs. Rural)	0.16	0.06	0.03 to 0.28	2.518	0.012
	calendar year (per year)	0.04	0.01	0.03 to 0.05	6.663	<0.001
	photoperiod length (per hour)	-0.06	0.03	-0.11 to -0.01	-2.197	0.029
	sex: Male (vs. Female)	0.14	0.06	0.03 to 0.26	2.403	0.017
	age (per year of age)	0.00	0.00	-0.01 to 0.01	0.148	0.882
	group x calendar year: Urban	0.00	0.01	-0.02 to 0.02	-0.214	0.831
	group x photoperiod length: Urban	0.00	0.04	-0.08 to 0.07	-0.035	0.972
	calendar year x photoperiod length	0.01	0.01	-0.01 to 0.02	0.999	0.318
	sex x age: Male	0.00	0.01	-0.01 to 0.01	0.741	0.459
	group x year x photoperiod: Urban	-0.01	0.01	-0.02 to 0.01	-0.661	0.509

Table S2 (cont.). LMEM and GLMEM models' results for sleep variables.
(*) Intercepts for sleep timing variables are expressed in hours elapsed since 00:00 on a given day. For example, a sleep midpoint at 26.5 h represents 02:30 clock time (26.5 hours since midnight on the calendar date of interest). Parameter estimates are added to or subtracted from this value accordingly in the LMEM.

Variable	Group	Photoperiod length	Year	Predicted	(clock time)	SE	95% CI	Δ (min)	ΔSE (min)	t	p value
Sleep onset (*)	Rural	11	2013	22.92	22:55	0.15	22.62 to 23.22	75	8	8.88	<0.001
	Rural	11	2023	24.18	0:10	0.10	23.98 to 24.37				
	Rural	13	2013	23.10	23:06	0.13	22.85 to 23.35	87	7	12.60	<0.001
	Rural	13	2023	24.56	0:33	0.10	24.36 to 24.75				
	Urban	11	2013	22.85	22:51	0.19	22.47 to 23.23	74	11	6.66	<0.001
	Urban	11	2023	24.08	0:05	0.12	23.84 to 24.33				
	Urban	13	2013	23.01	23:01	0.14	22.74 to 23.28	91	8	11.39	<0.001
	Urban	13	2023	24.52	0:31	0.12	24.28 to 24.77				
Sleep offset (*)	Rural	11	2013	32.21	8:13	0.15	32.51 to 8.13	12	8	1.44	0.151
	Rural	11	2023	32.41	8:24	0.10	32.61 to 8.24				
	Rural	13	2013	31.48	7:29	0.13	31.73 to 7.29	34	7	4.93	<0.001
	Rural	13	2023	32.04	8:03	0.10	32.24 to 8.03				
	Urban	11	2013	31.24	7:15	0.19	31.62 to 7.15	61	11	5.09	<0.001
	Urban	11	2023	32.16	8:09	0.13	32.41 to 8.09				
	Urban	13	2013	30.69	6:41	0.14	30.97 to 6.41	76	8	9.80	<0.001
	Urban	13	2023	31.96	7:57	0.13	32.21 to 7.57				
Midpoint of sleep (*)	Rural	11	2013	27.63	3:38	0.13	27.89 to 3.38	45	7	6.28	<0.001
	Rural	11	2023	28.39	4:23	0.10	28.58 to 4.23				
	Rural	13	2013	27.35	3:21	0.12	27.58 to 3.21	62	6	10.15	<0.001
	Rural	13	2023	28.39	4:24	0.10	28.58 to 4.24				
	Urban	11	2013	26.91	2:54	0.17	27.24 to 2.54	70	9	7.47	<0.001
	Urban	11	2023	28.08	4:05	0.12	28.31 to 4.05				
	Urban	13	2013	26.77	2:46	0.13	27.02 to 2.46	86	7	12.57	<0.001
	Urban	13	2023	28.20	4:12	0.12	28.44 to 4.12				

Table S3. Post-hoc contrasts based on model-predicted values for 2013 and 2023.
(*) Sleep timing variables are expressed in hours elapsed since 00:00 on a given day. For example, a sleep midpoint at 26.5 h represents 02:30 clock time (26.5 hours since midnight on the calendar date of interest).

Variable	Group	Photoperiod length	Year	Predicted	SE	95% CI	Δ	ΔSE (min)	t (z for SD)	p value
Sleep duration (h; Δ in min)	Rural	11	2013	9.31	0.13	9.06 to 9.57	-67	8	-8.29	<0.001
	Rural	11	2023	8.20	0.07	8.07 to 8.32				
	Rural	13	2013	8.40	0.09	8.21 to 8.58	-56	6	-9.57	<0.001
	Rural	13	2023	7.44	0.06	7.32 to 7.56				
	Urban	11	2013	8.66	0.17	8.32 to 9	-26	10	-2.48	0.013
	Urban	11	2023	8.23	0.08	8.07 to 8.39				
	Urban	13	2013	7.90	0.12	7.68 to 8.13	-19	8	-2.54	0.011
	Urban	13	2023	7.58	0.08	7.43 to 7.74				
Sleep regularity index (units)	Rural	11	2013	85.3	2.3	80.8 to 89.8	-7.2	2.4	-3.01	0.003
	Rural	11	2023	78.1	1.0	76.1 to 80				
	Rural	13	2013	85.7	1.6	82.4 to 88.9	-6.9	1.9	-3.58	<0.001
	Rural	13	2023	78.7	1.0	76.8 to 80.7				
	Urban	11	2013	77.3	2.8	71.8 to 82.7	-7.0	2.8	-2.50	0.013
	Urban	11	2023	70.3	1.2	68 to 72.6				
	Urban	13	2013	90.1	2.1	85.9 to 94.3	-20.8	2.7	-7.72	<0.001
	Urban	13	2023	69.3	1.3	66.8 to 71.8				
Standard deviation of sleep onsets (#)	Rural	11	2013	-0.09	0.08	-0.26 to 0.07	0.37	0.09	4.06	<0.001
	Rural	11	2023	0.27	0.05	0.17 to 0.38				
	Rural	13	2013	-0.26	0.06	-0.38 to -0.13	0.47	0.07	6.55	<0.001
	Rural	13	2023	0.21	0.04	0.13 to 0.3				
	Urban	11	2013	0.05	0.10	-0.14 to 0.24	0.40	0.10	3.87	<0.001
	Urban	11	2023	0.45	0.06	0.33 to 0.57				
	Urban	13	2013	-0.06	0.09	-0.24 to 0.11	0.40	0.10	3.88	<0.001
	Urban	13	2023	0.33	0.06	0.22 to 0.45				

Table S3 (cont.). Post-hoc contrasts based on model-predicted values for 2013 and 2023.
(#) Predicted values from gamma-distribution GLMEM using log scale - not actual SD values.

Campaign	Group	Participants	First time
2012 Spring	Rural	14	14
2012 Spring	Urban	6	6
2013 Fall/Winter	Rural	8	6
2013 Fall/Winter	Urban	11	10
2014 Fall/Winter	Rural	5	1
2014 Fall/Winter	Urban	6	4
2016 Winter	Rural	43	32
2017 Winter/Spring	Urban	17	12
2018 Spring	Rural	11	2
2018 Spring	Urban	15	8
2023 Fall/Winter	Rural	20	12
2023 Fall/Winter	Urban	19	11
2023 Spring	Rural	29	6
2023 Spring	Urban	19	4
2024 Summer	Rural	29	0
2024 Fall/Winter	Rural	26	11
2024 Fall/Winter	Urban	20	3
2024 Spring	Rural	41	10
2024 Spring	Urban	22	5

Table S4. Number of participants per field campaign and group including how many participants were included for the first time in each campaign.

# of campaigns	Group	Participants	% within group	Total	% from total
1	Rural	43	45.7	76	48.7
	Urban	33	52.4		
2	Rural	20	21.3	32	20.5
	Urban	12	19.0		
3	Rural	5	5.3	11	7.1
	Urban	6	9.5		
4	Rural	7	7.4	13	8.3
	Urban	6	9.5		
5	Rural	16	17.0	18	11.5
	Urban	2	3.2		
6	Rural	1	1.1	3	1.9
	Urban	2	3.2		
7	Rural	2	2.1	4	2.6
	Urban	2	3.2		

Table S5. Distribution of participants who were part of one or more campaigns.
Note: nobody participated in more than 7 campaigns.