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Taking the sleep lab to the field: Biometric techniques for quantifying sleep and circadian rhythms in humans

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Abstract

Objectives: Remarkably, the specifics of sleep along the human lineage have been slow to emerge, which is surprising given our distinct mental and behavioral capacity and the importance of sleep for individual health and cognitive performance. Largely due to difficultly of measuring sleep outside a controlled, clinical, and laboratory study in ambulatory individuals, human biologists have yet to undergo a thorough examination of sleep in ecologically diverse settings. Here, I outline the procedures and methods for generating sleep data in a broader ecological context with the goal of facilitating the integration of sleep and circadian analyses into human biology research.

Methods: I describe the steps involved in participant recruitment, screening by way of survey instruments, and sample collection. In addition to describing field use of the traditional (but invasive) equipment such as the gold-standard application of electroencephalography (EEG), I demonstrate leading-edge non-invasive techniques for biometric devices (ie, wrist-worn actigraphy, ring worn arterial pulsometry) to generate sleep and circadian rhythms data.

Results: I outline best approaches to process and analyze data—including variables such as sleep duration, 24-hour sleep time (ie, summation of night and day sleep), sleep efficiency, sleep fragmentation, and nonparametric circadian rhythms analysis to quantify circadian amplitude. Finally, I discuss comparative statistical methods that are optimized for the use of time-series data.

Conclusions: This review serves as an introduction to the best practices for studying sleep-wake patterns in humans—with the goal of standardizing tools for launching new human sleep biology research initiatives across the globe.

1 | INTRODUCTION

Sleep evolved to become one of the most widespread features shared by all life on Earth (Schmidt, 2014) and typically occupies approximately one-third of the human lifespan, yet a wholistic understanding of sleep in the human lineage has been slow to emerge (Nunn & Samson, 2018; Samson & Nunn, 2015). In large part, this is an artifact of sleep being a remarkably complex phenomenon that has been described as a behavior, a brain state, and a physiological process (Vyazovskiy & Delogu, 2014; Webb, 1988). Thus, early approaches to empirically measuring sleep relied upon the quantification of brain states by recording the electrical activity of the human brain. The conditions in which this can occur, until only recently, have been limited to controlled laboratories—therefore rendering the study of sleep in ecologically diverse environments relevant to the study of human biology a very challenging task. Pioneering efforts to comparatively explore the ecology of human sleep by

Worthman and colleagues (Worthman and Melby 2002, Worthman 2008, Worthman and Brown 2013) and the evolutionary-ethologically informed work of McKenna and colleagues (McKenna 1986, McKenna, Mosko et al. 1990, McKenna, Thoman et al. 1993, McKenna, Mosko et al. 1994, McKenna 1996, McKenna 1997, McKenna and McDade 2005, Gettler and McKenna 2011) described the importance of sleep arrangements and infant-mother cosleep. Until these ground-breaking works, sleep scarcely figured in the human evolutionary biology literature.

Using electroencephalography (EEG) to detect the electrical activity of the sleeping brain, one can observe shifts between qualitatively and quantitatively different states—nonrapid eye movement (NREM) and rapid eye movement (REM) sleep (Saper, Fuller, Pedersen, Lu, & Scammell, 2010). NREM sleep is subdivided into two stages: (a) Light N2 (NREM stages 1-2) accompanied by electrically detected sleep spindles (associated with information parsing and transference of information into long-term memory stores) and a K-complex (a waveform that suppresses cortical arousal in response to stimuli and aid memory consolidation). N2 sleep is associated with the lowest arousal threshold where a sleeping individual is easily awakened. This is to be differentiated from (b) deep N3 slow-wave activity (SWA; NREM stage 3) that is characterized by delta rhythms and slow, global cortical oscillations. When in this stage, a sleeping human is characterized by a greater arousal threshold compared to light sleep, making it typically more difficult to awaken (Ackermann & Rasch, 2014; Vyazovskiy & Harris, 2013).

REM sleep (often referred to as "paradoxical sleep") is associated with complete behavioral paralysis (with the exception of myoclonic twitches which are brief and discrete construction of the muscles), yet greatly active neural pattern comparable to an electrically active brain. REM sleep typically shows faster theta rhythms that arise from bidirectional interactions between the cortex and subcortex (Huber, Deboer, & Tobler, 2000; Nishida, Pearsall, Buckner, & Walker, 2009). Intriguingly, REM sleep can be distinguished by substages known as tonic and phasic REM. Tonic REM is characterized by widespread, low-voltage, fast electrocortical activity. In contrast, phasic REM is characterized by well-known oculomotor activity and concomitant cardiorespiratory irregularities (Sallinen, Kaartinen, & Lyytinen, 1996). To summarize, modern human sleep research using polysomnography (PSG) has revealed three discrete sleep stages: Light N2 sleep, deep N3 SWA, and REM (tonic and phasic) sleep (Ermis, Krakow, & Voss, 2010; Vyazovskiy & Delogu, 2014), all of which is regulated by preceding activity history (Achermann, Dijk, Brunner, & Borbely, 1993) and circadian time (Fisher, Foster, & Peirson, 2013).

Box 1

Key points for applying actigraphy in the field

Place actigraphy watch on the nondominant hand

Remind individuals to wear the watch continuously and that the sensors are robust under heavy use (even bathing and high levels of activity)

Remind individuals daily to use the event marker to self-record any sleep-related event (daytime napping or nighttime sleep)

Expect data loss (individuals will take off watches), equipment failure, and loss of actigraphy sensors. Build it into your study design with extra days of data generation

When using the external light sensors equipped with some actigraphs, it is critical that the light sensor not be covered by the person's sleeve. The sleeve can be tucked under the actigraph or clipped to a cuff or collar to increase light sensor exposure

Modern sleep science is the result of major technological innovation that began in the early 20th century. Notably, in 1928 the German psychiatrist Berger (1930) used electrodes to record the electrical activity of the human brain and unequivocally demonstrated the difference between being asleep and being awake. Berger, continuously and without disturbing the sleeper, recorded these signals and called them "electroencephalograms," and this finding launched a scientific interest in sleep. After World War II, implantable electrodes were developed and sleep research using animal models became commonplace. At the University of Chicago, a professor of physiology, Nathaniel Kleitman, assigned a graduate student named Eugene Aserinsky to ascribe behaviorally observable phenomenon in sleeping humans while simultaneously recording brain activity with EEG. The seminal paper by Aserinsky and Kleitman (1953) did not attract much attention until several years later due to the inherent challenges in time, energy, and resources cost of all-night observations. Staying up at night to study sleep remained—and still today remains—a challenging and undesirable method of research (Pelayo & Dement, 2017).

With the advent of the miniaturization of microprocessors, cost-effective activity monitors (founding the

study of activity now called actigraphy; Table 1) have been available since the early 1990s. Contemporary actigraphs include a movement detector called an accelerometer and are accompanied by the memory storage which can retain digitized information for long periods of time. The added development of water-resistant casings has ensured that actigraphs need not be removed by participants who are bathing or swimming. Therefore, by the 2000s, devices that could continuously generate 24-hour recordings over several weeks became increasingly affordable and more applicable to scientific applications (Stone & Ancoli-Israel, 2011).

Not long after actigraphy's development, and the theoretical groundwork provided by McKenna (1996) and Worthman and Melby (2002) the first anthropological study of sleep in a small-scale society took place in Papua New Guinea (Siegmund, Tittel, & Schiefenhovel, 1998). Interestingly, due in part to the costs associated with field application, the use of actigraphy by human biologists interested in studying sleep outside of economically developed countries did not take hold until after a study by Knutson (2014) in rural farmers in Haiti. Notable studies include the investigation of sleep in small-scale societies in the Toba/Qom horticulturalists (de la Iglesia et al., 2015), small-scale agriculturalists with no access to electricity (Samson et al., 2017d), reports of the first-ever comparative study of equatorial hunter-gatherers (Yetish, Kaplan et al. 2015, Samson, Crittenden et al. 2017b, Samson, Crittenden et al. 2017c), and the first publication on the sleep of agropastoralists in the Himba of Namibia (Prall, Yetish, Scelza, & Siegel, 2018). Numerous research groups are now studying sleep in remote field locations (Beale et al., 2017; Moreno et al., 2015; Pilz, Levandovski, Oliveira, Hidalgo, & Roenneberg, 2018; Smit, Broesch, Siegel, & Mistlberger, 2019)—and research questions targeting sleep-wake regulation as a response variable are not only limited to human biology, psychology, and evolutionary anthropology but is a useful, underexplored variable for transdisciplinary comparative work. Combined, these data provide a small, but critical sample from which to test hypotheses related to human sleep ecology and evolution.

TABLE 1 Definition of key terms

Term	Definition
Actigraphy	A noninvasive method that uses a small actimetry sensor to measure gross motor activity and algorithmically assesses rest-activity cycles
Polysomnography	A multiparametric test using primarily electroencephalography (EEG) measuring brain activity, electrooculography (EOG) measuring muscle twitching associated with eye movement, and electromyography (EMG) measuring skeletal muscle activation to study sleep
Circadian rhythm	An endogenous and entrainable 24-hour oscillating process that regulates the sleep-wake cycle
Chronotype	A heritable behavioral propensity to sleep during a particular phase during a circadian period, often described as *eveningness* (delayed sleep period) vs *morningness* (advanced sleep period)
Scotoperiod	The phase of darkness or absence of daylight throughout the circadian period
Photoperiod	The phase of light or absence of darkness throughout the circadian period
Sleep duration	The duration of time spent asleep within the night-time scotoperiod
Sleep quality	An overall measure using multiple modalities of sleep parameters to assess general sleep health. Specifically, it can be accessed via survey instruments (self-report), PSG, and actigraphy (typically via sleep efficiency and sleep fragmentation)
Polyphasic sleep	A behavior of multiphase sleep periods, usually more than two (biphasic sleep) or one consolidated bout (monophasic sleep), throughout the circadian period.

2 | TECHNIQUES FOR SLEEP AND CIRCADIAN MEASUREMENT

Sleep detection methods are varied and numerous. Figure 1 illustrates a taxonomy of sleep detection methods developed from a comprehensive methodological review (Ibáñez, Silva, & Cauli, 2018). For sleep detection in dynamic field environments typical for human biology, ecology, and anthropology, only a small number of these methods are practical and are often need significant alterations to address communication barriers when working with indigenous populations. Research fatigue, in communities that have a long history of human biological research, can also serve as a challenge to generating comprehensive datasets comparable to research in economically developed countries. Here, I present the sleep detection methods that are most useful in field environments.

2.1 | Polysomnography

The current "gold standard" for sleep research remains PSG, which incorporates electroencephalogram (EEG),

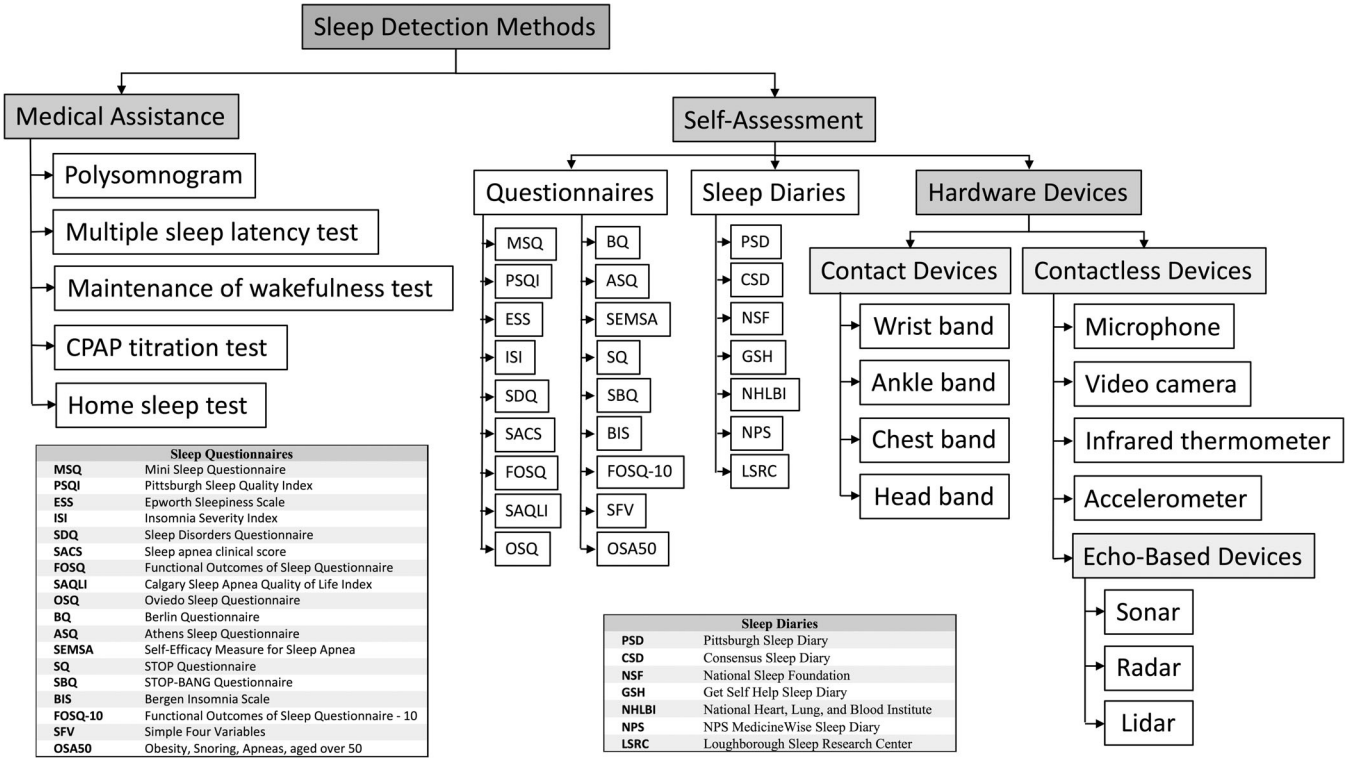

FIGURE 1 Taxonomy of sleep detection methods. White boxes represent sleep assessment methods or technologies currently used to determine sleep states, whereas gray boxes represent the methodological category the technology falls under. CPAP, continuous positive airway pressure.
Figure adapted from Ibáñez, Silva et al. (2018)

electrooculogram (EOG), and electromyogram (EMG) to generate multiple channels of data used to quantify sleep and its stages (known as sleep architecture). It is primarily used in clinical contexts in sleep labs and depending on the needs or symptoms of patients seeking medical care for sleep disturbances, multiple added measures (eg, respiration, heart rate, tibialis muscle movement, oximetry) can be applied. The EEG, EOG, and EMG records can be scored for sleep stages throughout NREM and REM and typical values generated are total sleep time, total wake time, sleep onset latency, and percent time in REM vs NREM sleep. Clinically, the data generated by PSG are crucial for certain types of diagnoses (especially respiratory sleep disorders, and also for nonrespiratory sleep disorders such as a class of sleep disorders known as hypersomnias that include narcolepsy, Kleine-Levin syndrome, and idiopathic hypersomnolence).

However, PSG has the distinct drawback in its invasive nature which typically produces a second night adaptation effect, where participants sleep disrupted in the first night during the habituation period (Hertenstein, Gabryelska et al. 2018). The recording process and the sterile conditions of many sleep laboratories may disturb the participant's sleep. Moreover, PSG studies, which require highly trained shift working technicians, are very costly to accomplish. In addition, PSG typically provides data generated during the major sleep bout in the scotoperiod (defined as the nighttime interval without sunlight; see Table 1), lasting 6-10 hours, and therefore little information is available about daytime photoperiod sleep (commonly called napping behavior). Most PSG units are large and cumbersome, but mobile PSG has been developed (designed originally for home use for clinical contexts) that makes its application possible in remote field settings. PSG also has an established "first night effect" where individuals habituate to sleeping with the equipment and thus may not capture the participants' normative sleep expression. It requires significant battery power and needs to be coupled with the minimum acceptable electrode montage (Duce, Rego, Milosavljevic, & Hukins, 2014) to be functional in the field. Despite the remaining challenges, mobile PSG units have been adapted in at least one study of sleep in a small-scale society (Figure 2B,C), although due to the inherent difficulties in using PSG in the field, sample sizes for the number of nights and individuals remained small (Samson, Manus, et al., 2017d). Finally, videosomnography is a technique commonly coupled in clinical sleep studies in combination with automated movement sensors. Moreover, in locations where

FIGURE 2 Field application of actigraphy and polysomnography. (A) Actigraphy is an easy to apply, noninvasive method to measure sleep, activity, and lux in ambulatory participants. It can be administered by a single researcher, and data are continuously recorded throughout the duration of the study. (B) Polysomnography is challenging to apply in field environments; it often requires the help of multiple research assistants and requires administration before the participant goes to bed and removal as soon as the participant wakes up the following morning. (C) Polysomnography takes 45-60 minutes to apply to participants and can be cumbersome for individuals in dynamic environments. (Photos credited to author)

participants have ready access to the power grid and internet via homes, hospital wards, or lab settings it can be useful for sleep quota determination and social sleep (especially infant-mother dyads) measures—as has been performed in work from biological anthropologists in postindustrial contexts (Ball & Klingaman, 2008; Ball, Tomori, & McKenna, 2019). There are a few limitations for using videosomnography in small-scale societal field settings; first, battery life is difficult to sustain over the course of a night (for the generation of a complete night's hypnogram) where the camera is powered over ethernet (as has been the case for primate videographic sleep studies (Samson and Shumaker 2013)); second, if the aim is to generate normative sleep data, the intrusive nature of videographic recording may modify otherwise natural nighttime behaviors.

In summary, PSG is the only reliable technology that can discriminate between sleep stages by measuring brain activity directly but is affected by key limiting factors including high cost, arduous application, intrusiveness to sleep, and the typical requirement of a sleep laboratory and its dedicated infrastructure (Razjouyan et al., 2017).

2.2 | Actigraphy

Actigraphy, in contrast to PSG, is much less expensive and cumbersome and because it provides 24-hour recordings of activity, it is the most widely applicable method for studying sleep in diverse ecologies. Actigraphs (also called actimeters) use piezoelectric film to measure

activity and typically record limb movement (although chest actigraphs also can be used). Sleep is scored by using the raw activity data generated by the actimeters and discrimination of sleep-wake states can be determined by algorithms that have been validated against PSG. Despite being vulnerable to overestimation of sleep states (de Souza et al., 2003), actigraphy has been validated against PSG, demonstrating substantial improvements over subjective, self-reports of sleep (Lauderdale, Knutson, Yan, Liu, & Rathouz, 2008). Traditionally, the actigraph is placed on the nondominant wrist (Figure 2A) but under certain circumstances (eg, where injury has occurred, where individuals prefer to use one hand over the other if it impedes work, in infant sleep studies), alternative wrist or leg actigraphs are viable and ideal for use (Gershoni-Banich, Epstein, Tzischinsky, Lavie, & Brandes, 1994). Multiple research groups validating actigraphy against PSG have demonstrated that when worn on both wrists, the activity data generated from the two were equivalent (Sadeh, Sharkey, & Carskadon, 1994). Physical movement generally is sampled several times per second and stored in 1-minute epochs, although sampling and epoch rates can be predetermined to be of greater or lesser resolution by the investigator (Stone & Ancoli-Israel, 2017). The generated data are downloaded and displayed on a computer and using equipment specific software, are later examined and scored for sleep-wake determinations per epoch of analysis. A standard output generated by most analytical software associated with actigraphs is the actogram (Figure 3).

When data are generated for periods longer than a week, it is recommended to download the data to minimize the risk of data loss. Batteries are the most common cause of data loss, and battery levels should be routinely checked after long-term storage and before application in the field, and again during any subsequent downloading. Only keep batteries with levels above 90%, as they are of particular risk of failure if below a certain voltage threshold. Although manufacturers claim up to 90-day battery life for particular units, in application, 30 days is often the approximate duration in which batteries can be expected to perform with minimal data loss. It is recommended to keep a battery log recording the battery serial number, initialization date, date of previously downloaded data, the sum of days the battery has been

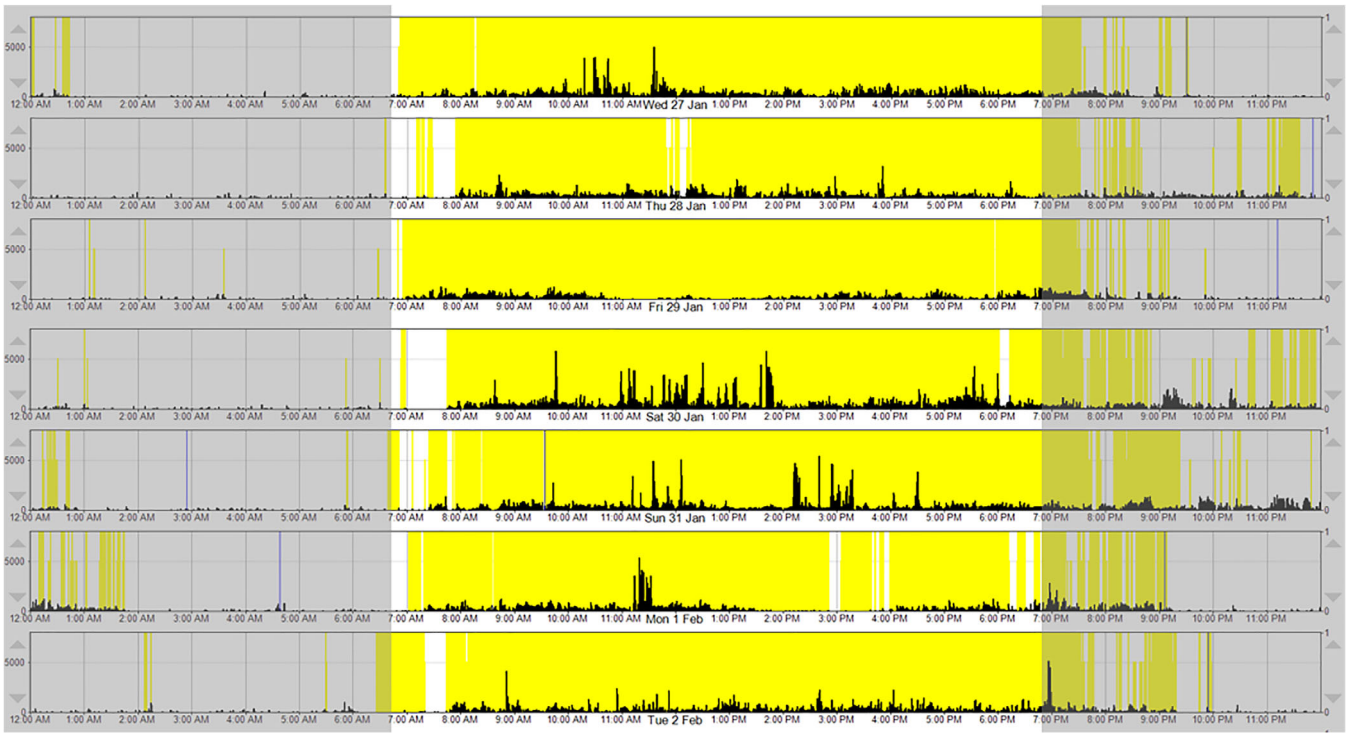

FIGURE 3 Twenty-four-hour activity histogram (actogram). An actogram with associated recorded light throughout a week span for a 26-year-old Hadza male. The shaded area represents the mean photoperiod during the study. Yellow represents lux exposure, whereas black represents raw activity. The light sensor records white light with a response optimized to match the human eye and the light is sampled once per second and averaged over the 1-minute epoch. The data are stored as lux values. Additionally, in equatorial communities where long sleeve clothing is rare (which could conceal the lux monitor), the graph illustrates that light exposure is common during the night and fire or moonlight are the only sources of light available to participants who are actively exposed to their environments.
(Actogram originally reported in Samson, Crittenden et al., 2017b)

active, and start and end voltage (Stone & Ancoli-Israel, 2017). Finally, data loss can occur due to participant removal of watches; actively reminding participants during daily interviews to not remove the watch can improve compliance; otherwise, data will need to be manually removed post hoc with data editing by way of the watches software.

When actigraphy is used in field environments where multiple investigators are administering the sensors for use, it is recommended that an overall data quality plan is developed that standardizes protocols for distribution and retainment of actigraphs. Rarely, participants with skin sensitivity may be advised to remove the bands for a few minutes per day to avoid pressure sores. If this occurs, the time the device is removed and replaced, and the duration in which the watch was not worn should be logged. This information will be useful when editing the data before analysis. Although the advantages of using actigraphy are numerous, there are limitations (Ancoli-Israel et al., 2003). When compared with PSG, actigraphy is excellent at detecting total sleep duration and is more reliable when used in healthy normal adult participants. Yet, individuals with sleep disorders should be screened by way of survey instrumentation since actigraphy recordings become less accurate as sleep becomes more disturbed. In general, actigraphy may overestimate sleep and this is particularly the case with daytime analysis. Given the paucity of data in small-scale or non-industrialized and economically developing populations, targeting healthy adults has historically been the primary objective of most sleep research in this context. Yet, recent work has been performed with respect to infant-mother cosleep (Ball et al., 2019; Crittenden et al., 2018; Vitzthum, Thornburg, & Spielvogel, 2018). As more data fill in the gaps of what is known about sleep in healthy adults, exciting future research should focus on the ontogeny of sleep and development of sleep disorders in pediatric and elderly participants.

2.3 | Participant recruitment

As known by most human biologists and anthropologists, local liaisons are critical for undergoing research projects involving human participants in field environments. For many anthropologists who have ongoing research projects in collaboration with communities, integrating actigraphy into concurrent and future studies can be done by adding additional survey instrumentation and then using the application of actigraphy. More challenging is the initiation of research with new communities, where principle investigators must engage in grass-roots community outreach. In general, recruitment for study participants can have three approaches: (a) flyers can be placed explaining the sleep studies at village stores (the Grocery, the Community Center, local restaurants); (b) researchers can use snowball or nonprobability sampling, a common strategy used to recruit participants based on relationships (Trotter II 2012); (c) Most importantly within an indigenous context is working with self-identified Elder volunteers in the community. Information sessions should occur during pilot projects within the community to explain the study, discuss the components with those interested, and answer any questions or concerns. Liaisons, usually local college or university faculty with longstanding community relationships, local health and/or government officials can help arrange town hall meetings. As a special note, working with indigenous communities takes care and recent methods have been forwarded to engage in responsive community research models grounded in the local indigenous ways of knowing (Healy and Tagak Sr 2014).

In complex societies without clearly bounded, self-identified groups, participant recruitment requires different kinds of considerations. One strategy is to devise a site-based sampling process where the investigator identifies a group of participants with the characteristics needed for the study by contacting community gatekeepers. Within the population of interest "sites" are places with organizations such as churches, community centers, social clubs, clinics, and service groups, in addition to residential areas such as housing projects or apartment buildings. Investigators can compile a list of sites per population of interest so that every member of the population is a member of at least one site and then contact gatekeeper liaisons for each site. Finally, investigators can then gain access to the study community through contact with the sites liaisons (Arcury & Quandt, 1999).

2.4 | Survey instruments and guided self-assessment of sleep

One of the most important tools for any human biologist is survey instrumentation. As shown in Figure 1, there are numerous sleep surveys that target self-assessment of subjective sleep, and most of the variation derives from the survey attempting to assess a specific sleep disorder.

The preliminary evaluation of sleep can be completed with a sleep questionnaire. They are ideal in field use because they are an inexpensive and rapid test, and thus ideal for the first screening of sleep disorders. Moreover, they quantitatively summarize the participant's perception of their own sleep quality. Because they are subjective, sleep questionnaires can be influenced by bias and inaccuracy, yet their subjectivity does not necessarily

Box 2

Common survey questions for field contexts

1. How many hours do you sleep per night? (Answer: <6, 6-8, >6)
2. Is your sleep: (Answer: Not enough/Just enough/Too much)
3. Do you fall asleep quickly? (Answer: Yes/No)
4. Are you happy with your sleep? (Answer: Yes/No)
5. Where do you sleep? (Inside/Outside)
6. Do you sleep with other people? (Answer: Yes/No) If so, how many?
7. If you sleep at night, how many times do you arouse or wake? (Answer: Never/Once/Twice/More than twice)
8. Do you "nap" or sleep during the day? (Answer: Yes/No) If yes, how many times?
9. Do you have any sleep problems? (Answer: Yes/No)

render questionnaires inaccurate, and many hold up well in validation studies with PSG. Because field sleep studies are mainly generating basic sleep parameters, the Pittsburgh Sleep Quality Index (PSQI) questionnaire (Buysse, Reynolds, Monk, Berman, & Kupfer, 1989) is particularly important to serve as a template for field-specific surveys working with indigenous or at-risk populations. The PSQI has nine items (four-point scale) and many questions are readily adaptable to field contexts; in addition, it is important to highlight how the interpretation of different components allows for an in-depth sleep analysis, which if not appropriately performed can limit the objectivity of the results (a good example of a fully utilized PSQI is work from Sochal, Małecka-Panas et al. (2020)). Core questions to include at the onset of a study are listed in Box 2. Every field site is different and will require tailoring to suit research questions and study aims. Experts in the local language and culture should edit the document to ensure it is as clear and concise a series of questions as possible. For an extended list of the sleep questionnaires used in the last 30 years of sleep research, see the public repository developed by Ibanez, Silva, and Cauli (2018) where such surveys can be downloaded at http://personales.upv.es/josilga/sleep/.

Sleep diaries are common practice in sleep studies in economically developed countries and allow participants to self-assess their sleep. Sleep diaries have one important advantage over sleep questionnaires in that while sleep questionnaires are filled in once, sleep diaries are filled in over a period of time, generally throughout the study period. Therefore, sleep diaries provide higher resolution data by providing data each day of the study and because they are often filled in just after waking up, they are not as dependent on memory recall. For a comprehensive list of sleep diaries see http://users.dsic.upv.es/jsilva/Sleep/. It is recommended that sleep diaries are personally administered by the principle investigator or research assistants with daily or bi-daily visits to study participants.

2.5 | Alternative biometrics

There are numerous commercial devices that, when combined with smartphone apps, provide various types of sleep assessment data. To date, there are more than 100 000 apps in both the Google Play and Apple apps stores, many of which measure sleep using proprietary sleep detection algorithms. The quality of the sensors is the primary factor that influences the accuracy of sleep detection devices. Another critical factor is the software that processes the data collected by the sensor and as a consequence, the same device (eg, a mobile phone with a piezoelectric film [i.e., accelerometer] that is used as a sensor) can produce different results depending on the software used for data processing. Therefore, not only is it that most of the publicly available sleep apps have not been clinically validated, but since they rely on mobile phones and a reliable internet connection, they are often not appropriate for studies in remote field locations. Typically, these apps are implemented and maintained by independent (nonclinical) programmers and, thus, their clinical and research use is not recommended until further validation work has occurred. Numerous reviews demonstrate the current understanding of app validation (Evenson, Goto, & Furberg, 2015; Jeon & Finkelstein, 2015; Kolla, Mansukhani, & Mansukhani, 2016).

Of critical importance to the "bring the field to the lab" approach for field site sleep studies is the validation of new technology that can be used in both lab and field environments with instruments that are precise enough to detect participant sleep staging in both NREM and REM. Currently, actigraphy cannot distinguish between NREM and REM so there are inherent limitations to the types of research questions that can be addressed with this technology. With the burgeoning biometric market, there are promising developments in wearable device designs such as the arterial pulsometric *OURA* rings to assess sleep. Evaluations of the performance of the *OURA* ring (de Zambotti, Rosas, Colrain, & Baker, 2019) as a multisensory sleep tracker compared to PSG have shown that PSG-*OURA* differences for total sleep time and wake after

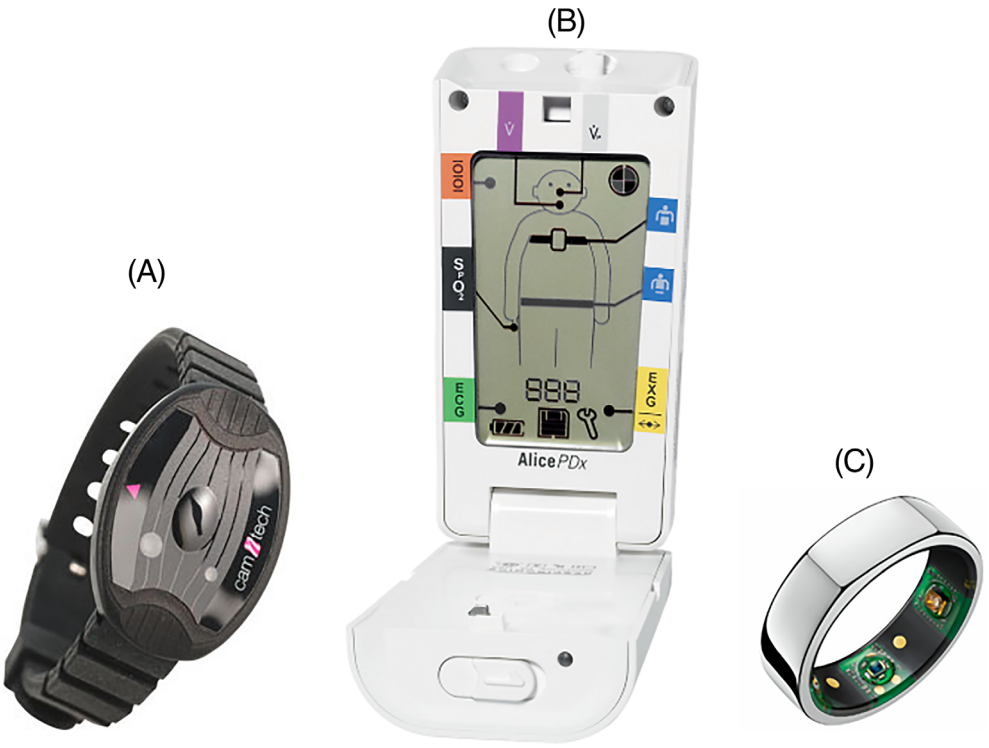

FIGURE 4 Equipment options to generate sleep quotes in field environments. (A) Actigraphy is low profile, relatively middle range cost, robust and easy to apply, yet does not capture sleep stages. (B) Polysomnography captures sleep stages, yet is difficult to apply with greater levels of research and participant fatigue and high in overall cost. (C) Biometric devices are the least costly, are less validated against polysomnography in field environments, require internet and app use, yet yield vast amounts of data

sleep onset lay within the less than 30 minute a priori-set clinically satisfactory ranges of 87.8% and 85.4%, respectively. The *OURA* ring had agreement of 65%, 51%, and 61% in detecting light N1 sleep, deep sleep (N2 + N3), and REM sleep, respectively, with an overall 96% sensitivity to detect sleep. The primary difficulty with respect to biometric devices in the field is power and internet limitations. The ring requires USB charging (approximately every 5 days), internet access, and smartphone linkage. As of yet, there are no desktop applications that can download and interface data collection, thereby limiting its research use in field contexts. The *OURA* ring has the potential for detecting outcomes beyond binary sleep-wake scoring and validation of the next generation rings will likely be of great value to clinical and field researchers alike. In summary, although mobile PSG, actigraphy, and biometric devices have tradeoffs (Figure 4), actigraphy remains the most practical, cost-effective, and reliable way to generate sleep quotas for field use.

3 | QUANTIFYING AND ANALYZING SLEEP USING ACTIGRAPHY

3.1 | Standardized nighttime sleep and daytime nap quotas

Using actigraphy for sleep detection classifies the sleep state of a participant at 1-minute epochs (although many actigraphs now can record at 30 second epochs). For most field applications, 1-minute epochs extend memory and are the most commonly used and reported, although 30-second epochs record at higher resolutions and may be more appropriate as memory capacity in actigraphs improves. Most sleep detection methods from actigraphy function to classify an epoch as "Awake" or "Sleep." For either 30-second or 1-minute epochs, the "medium" wake threshold is the most commonly used threshold setting for actigraphy studies (Meltzer, Montgomery-Downs, Insana, & Walsh, 2012). From this binary state classification method, one can produce several fundamental parameters that can be derived from the primary data (eg, sleep duration, sleep efficiency, sleep fragmentation, wake after sleep onset). The expanding literature on the human biology of sleep outside the laboratory can be characterized as lacking standardization with papers often reporting some variables and not others. It is critical that future research standardizes reports of descriptive sleep quotas as many of the most crucial research questions are comparative in nature.

One particularly salient issue is the best practices in applying actigraphy to assess daytime sleep. This is an increasingly critical measure as a fundamental question in human sleep biology has been how to best describe "natural human sleep" as either a single monophasic bout or a polyphasic sleep schedule consisting of multiple naps and one bout of night-time sleep (Samson, Crittenden et al. 2017a). In general, actigraphy is reliable at detecting naps but less reliable at detecting the absence

of naps (Kanady, Drummond, & Mednick, 2011). Thorpy (1990) defined a daytime nap as any short sleep episode outside of the nighttime sleep onset and offset period. Yet, methods for nap reporting in the literature have been highly varied and would benefit from standardization. For example, Yoon, Kripke, Youngstedt, and Elliott (2003) used this definition to report the percentage of participants that showed any napping behavior. Yetish et al. (2015) similarly reported the percentage of days in which participants napped, using automatic algorithmic detection of nap periods greater than 15 minutes, with the addition of manual review of actigraphy data to identify nap periods. Evans et al. (2011) reported Old Order Amish daytime sleep by percentage of individuals that had napped in the previous week.

In general, participant-reported naps have been found to be more accurate than actigraphy in determining discrete episodic events of daytime napping (Kawada, 2008). Yet, previous work has demonstrated that specific parameter settings used to identify nap duration and activity counts can impact sleep-wake determinations and that this is especially important in the field (Samson et al., 2016). There are two levels at which software parameter settings can be adjusted to improve the detection rate of naps with actigraphy. The first is at the level of raw movement data, hereafter referred to as counts. In the process of implementing a sleep-scoring algorithm (such as that described in (Cole, Kripke, Gruen, Mullaney, & Gillin, 1992), a value is imposed on the data to distinguish predicted sleep (score of 0) from predicted awake (score of 1) per epoch. That binary data are then secondarily scored according to the continuous 1 second and 0 second interval length. Out of six parameter settings tested, Samson et al. (2016) discovered only one parameter setting to reliably detect reported naps in Hadza hunter-gatherers (15-minute nap length, ≤50 counts). With these parameters in mind, Table 2 offers a recommended list of sleep measures to report in table format. In summary, naps are operationally defined as sleep scored outside the primary (ie, longest duration), scotoperiod sleep bout, and categorized by way of a combination of algorithmic detection where settings have been optimized to detect nap periods (to highlight to reviewers potential naps) and manual review (where the nap is visually assessed for accuracy), ultimately generating daily measures of both nap frequency and total duration of each nap in minutes.

TABLE 2 Best practice to report standardized sleep quota as descriptive statistics

Sleep measure	Definition
Sleep onset	The time when a participant has been recorded as falling asleep
Sleep end	The time when a participant has been recorded as waking up
Time in bed	The total elapsed time between the moment the participant entered bed and got out of bed
Sleep duration	The total time spent in sleep according to the epoch-by-epoch wake/sleep categorization
24-hour total sleep time (TTST)	The cumulative sum of sleep duration and total nap duration
Sleep latency	The time in duration between the moment when the participant entered bed and fell asleep
Wake after sleep onset (WASO)	Total sum duration of the periods of wakefulness occurring after recorded sleep onset, excluding the wakefulness occurring before sleep onset
Sleep efficiency	The percent of time scored as sleep during the total sleep period (Time in bed); calculated as 100% × sleep duration/the time between bedtime and get up time
Sleep fragmentation	The number of interruptions of sleep by physical movement; calculated as 100 × the number of groups of consecutive active epochs/by the total number of immobile epochs)
Nap frequency	The total number of naps recorded outside the primary (i.e., longest sleep bout) during the scotoperiod
Nap duration	The sum duration of time per nap
Cumulative nighttime activity	The total of all the activity counts during the assumed sleep period

3.2 | Standardized circadian quotas using actigraphy

An individual's preferred mean time of sleep onset and offset is called a chronotype and is a heritable trait (Lopez-Minguez, Ordoñana, Sánchez-Romera, Madrid, & Garaulet, 2015). Chronotype is also modified by life history, changing from late (ie, later sleep onset and offset times) during adolescence and adulthood to early in old age (Roenneberg, 2013; Roenneberg et al., 2004; Roenneberg, Wirz-Justice, & Merrow, 2003). Finally, the role of human culture as a regulator of chronotype has recently been explored, and evidence is emerging that it may also be a driver of sleep and activity timing throughout the circadian period in small-scale societies, including hunter-gatherers (Samson, Crittenden et al. 2017a, Samson, Crittenden et al. 2017c). Questionnaires, such as the Munich ChronoType Questionnaire are commonly

TABLE 3 Best practice to report standardized circadian-related metrics as descriptive statistics

Central phase measure (CPM)	The midpoint between sleep onset and awakening; expressed as minutes after midnight and thus can be reported as negative values for before midnight, 0 value at midnight, and positive values after midnight
Sleep midpoint	The midpoint of sleep onset and awakening; expressed as time within the 24-hour cycle
NPCRA intradaily variability (IV)	Quantifies the fragmentation of periods of rest and activity; ranges from 0 to 2 and typically is <1 for healthy adults, with higher values indicating a more fragmented rhythm
NPCRA interdaily stability	Degree of resemblance between the activity patterns on individual days; ranges from 0 to 1 and may typically be about 0.6 for healthy adults
L5	Average of the activity values for the five least active consecutive hours in the 24-hour cycle
M10	Average of the activity values for the 10 most active consecutive hours in the 24-hour cycle
NPCRA relative amplitude (RA)	Calculated by dividing amplitude by the sum of L5 and M10; ranges from 0 to 1, with higher values indicating higher amplitude of the rhythm
Circadian function index	Relative amplitude (RA), interdaily stability (IS), and intradaily variability are generated using NPCRA; CFI incorporates three parameters, IV, IS, and RA. IV values are inverted and normalized between 0 and 1, with 0 being a noise signal, and 1 a perfect sinusoid. Then, CFI is calculated as the average of these three parameters. Consequently, CFI oscillates between 0 (absence of circadian rhythmicity) and 1 (a robust circadian rhythm)

used in developed economies (Zavada, Gordijn, Beersma, Daan, & Roenneberg, 2005) but due to being directed toward wage-based labor practices, it oftentimes poorly translate to field contexts in developing economies or small-scale societies. Both the variables *sleep midpoint* which is the midpoint of sleep expressed as 24-hour time and the *central phase measure*, which is the midpoint of sleep expressed as an integer are excellent variables to generate and report that capture circadian timing of sleep (Table 3).

Nonparametric circadian rhythm analysis (NPCRA) is useful to overcome limitations inherent in actigraphy generated data because it can conform count data to a Cosine waveform shape (otherwise known as a Cosinor analysis). This method is used to analyze 24-hour data over several days (recommended to have more than 7 days of consecutive data) to determine the nonparametric variables that are valuable indicators of circadian rhythm amplitude, fragmentation, and consistency over time (Van Someren et al., 1999). When these conditions are met, it is advised to report NPCRA measures in table format (Table 3). This analytic technique generates circadian phase markers that permit the computation of the *relative amplitude* (RA), *interdaily stability* (IS), which provides an estimated measure of rhythm stability (ranging between 0 and 1) where 0 is Gaussian noise and where 1 is a perfect rhythm stability from one day to the next. *Intradaily variability* (IV) is an estimated measure of rhythm fragmentation, with values of 0 indicating a perfectly sinusoidal curve, and 2 Gaussian noise, respectively. Previous clinical work (Ortiz-Tudela, Innominato, Rol, Lévi, & Madrid, 2016) incorporated RA, IS, and IV into a single index variable to yield the *Circadian Function Index* (CFI), and descriptions of CFI calculation have been detailed elsewhere (Ortiz-Tudela, Martinez-Nicolas, Campos, Rol, & Madrid, 2010). CFI ranges between 0—an absence of circadian rhythmicity—and 1—a robust circadian rhythm (Table 3).

4 | TECHNIQUES FOR MEASURING ENVIRONMENTAL DRIVERS OF SLEEP

Two principle zeitgebers (ie, entrainment factors) that influence the timing of sleep in relation to circadian timing are light (via the master circadian clock known as the suprachiasmatic nucleus) (Ibuka, Shin-ichi, & Kawamura, 1977) and temperature (via cold and warm sensing neurons) (Siegel, 2011). There are many solutions to measuring meteorological variables in field environments—generally searchable through local government and scientific institutional data repositories; I have found the *Kestrel 5400 heat stress tracker* robust in field application. The metric for light is lux and sensors are commonly placed in actigraphs, although independent digital luxmeter sensors can be placed within the field site (*HDE Digital Luxmeter* with LCD display can measure lux to a 50 000 range). In addition, previous work has demonstrated direct evidence that the lunar cycle is linked to sleep-wake patterns in a hunter-gatherer society (Samson, Crittenden, Mabulla, Mabulla, & Nunn, 2018), suggesting that moonlight alters

TABLE 4 Key environmental variables to control for in models where sleep has been recorded in the field

Drivers of human sleep in field environments	General description	References
Dusk/dawn/photoperiod	Light is a primary circadian entrainment factor. Particularly, sunrise times prove to be predictive of wake times in multiple small-scale societies	Samson, Crittenden, Mabulla, Mabulla, and Nunn (2017a), Yetish et al. (2015)
Temperature	Because temperatures drop significantly during the night, and individuals tend to have little environmental buffering, increased temperature typically increases sleep duration	Samson, Crittenden, et al. (2017a)
Lux	Greater exposure to lux appears to reduce sleep duration	Samson, Crittenden, et al. (2017a)
Wet bulb global temperature (WBGT)	A measure of the *apparent* or "real feel" temperature of the environment; it is calculated by combining measurements of ambient air temperature, black globe temperature, and relative humidity as a percentage. Evidence suggests that sleep onset and offset times may be regulated by WBGT	Yetish et al. (2015), Manger personal communication
Lunar phase	Lunar phase has shown to be a driver of nighttime sleep-wake activity in a hunter-gatherer population	Samson et al. (2018)
Rainfall	Increased rainfall appears to reduce sleep duration	McKinnon, Samson, Nunn, and Nepomnaschy (2020)
Ambient noise	Typically, as continuous measures of activity are positively associated with increased activity throughout the circadian period; specifically, a pattern shown in one small-scale agricultural population demonstrates that high dB values are related to nighttime increases to activity	Samson, Manus, et al. (2017d)

sleep-wake patterns in the ways that differ from electric lighting. Lunar phase can be measured using astronomical data collected and retained by the United States Navy: (https://www.usno.navy.mil/USNO/astronomical-applications/data-services/phases-moon). Rainfall, which can differ seasonally, could influence sleep. To measure precipitation, apply a rain gauge (also known as udometer or pluviometer) to gather and measure the amount of liquid precipitation over an area in a predefined period of time (*Cole-Parmer Clear Rain Gauges* measures rain levels in both English or metric units). Moreover, ambient noise can interrupt sleep and can vary by population and density. Ambient decibels (dB) can be recorded using sound level meter data loggers (*Convergence instruments* crafts USB solar powered and waterproof loggers). Therefore, it is critical to control for environmental factors that have been shown to greatly influence sleep in small-scale societies (Table 4).

4.1 | Sleep and circadian data analysis

Actigraphy generates measures that can be used for sleep, chronobiology, and physical activity. Therefore, there are a number of ways in which researchers can analyze data to test hypotheses. Generally, each actigraphy device is accompanied by proprietary software designed to extract raw data into common data frame types (Table 5). To assess the predictors of sleep in field environments, it is recommended to use linear

TABLE 5 Sources of commonly used software and R packages for actigraphy data processing and analysis

Material	Function	Source
CamNtech MotionWare	Software interface to extract and process raw data from actigraphy device	https://www.camntech.com/motionware-software/
Philips Respironics Actiware	Software interface to extract and process raw data from actigraphy device	https://www.usa.philips.com/healthcare/sites/actigraphy/solutions/actiware
Ambulatory Monitoring Inc.	Software interface to extract and process raw data from actigraphy device	http://www.ambulatory-monitoring.com/soft_updates.html
Activinsights	Software interface to extract and process raw data from actigraphy device	https://www.activinsights.com/data-analytics/
Actigraph	Software interface to extract and process raw data from actigraphy device	https://actigraphcorp.com/support/software/
R package: *lme4*	Assesses the ecological predictors of sleep using a linear mixed effects models for sleep quota response variables	https://cran.r-project.org/web/packages/lme4/index.html
R package: *MuMIn*	Model averages with ΔAIC <10 and obtain models using shrinkage (full model averaging), thereby improving less certain estimates by pooling information from more certain estimates	https://cran.r-project.org/web/packages/MuMIn/index.html
R package: *actigraphy*	Specifically designed for actigraphy time-series data analysis by measuring raw activity counts within and between samples; this technique avoids summary statistics that can mask differences across groups	https://cran.r-project.org/web/packages/Actigraphy/index.html

mixed-effects models for the different types of sleep or circadian response variables using the *lme4* package. All models should control for factors such as age, biological sex, and the other variables shown in Table 4. Typically, nightly means are generated for each variable, and thus it is critical to include "participant" as a random effect (to control for repeated measures and variation in sample size), and obtain coefficients based on optimization of the log-likelihood using shrinkage. Shrinkage incorporates measurement error (ie, SE) into the regression model, which improves less certain estimates by pooling information from more certain estimates (McElreath, 2016). It is recommended to use the *MuMIn* package in R (Bartoń, 2015) to average models with ΔAIC <10 and interpreted models.

Another powerful technique is functional linear modeling (FLM) which can be used to characterize and illustrate 24-hour sleep-wake patterns relative to categorical or continuous measures (Figure 5). The FLM approach is specifically designed for actigraphy time-series data analysis and measures raw activity counts within and between samples. This is advantageous with actigraphy data because summary statistics (that average blocks of time together) can mask differences across groups (Wang et al., 2011), making FLM a powerful analytical tool. FLM can be applied as a nonparametric permutation test method in the R package *actigraphy* (Shannon et al., 2015). A further advantage of this method is that it does not rely on distributional assumptions. The *P*-value is calculated by counting the proportion of permutation *F* values that are larger than the *F* statistics for the observed data. It is recommended to use the point-wise test (with 500 permutations) that provides a curve that is the proportion of all permutation *F* values at each point in the time series (Wang et al., 2011).

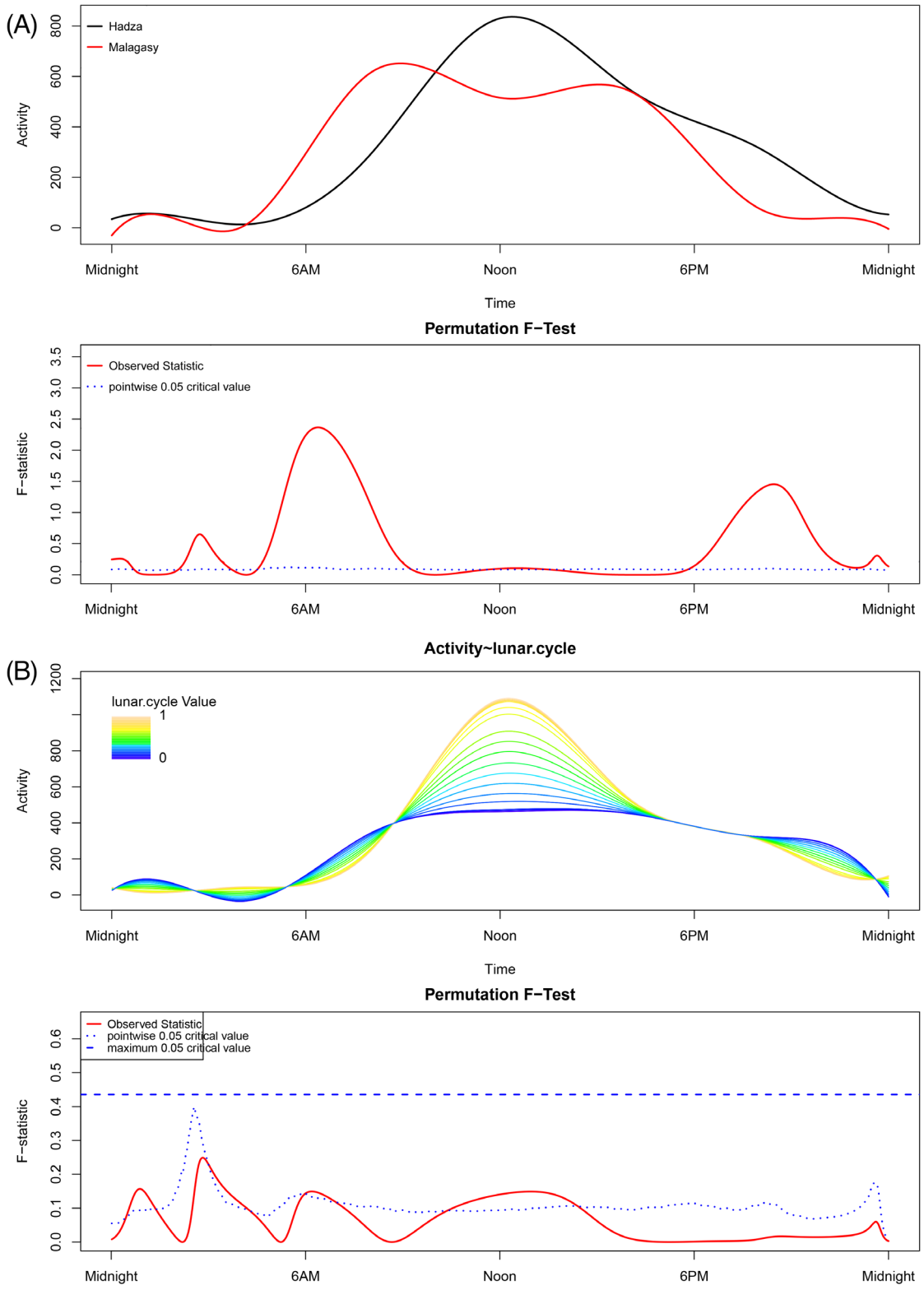

FIGURE 5 Functional linear modeling (FLM) output for both continuous and categorical variables. (A) A nonparametric permutation *F* comparing activity (*y*-axis) and the average nightly sound level (*x*-axis) between two populations. The point-wise critical value (dotted line) is the proportion of all permutation *F* values at each time point at the significance level of 0.05. When the observed *F*-statistic (solid line) is above the dotted line, it is concluded the continuous measures have significantly different mean circadian activity patterns at those time point. (B) The time series average demonstrated general patterns that show a continuous activity measure associated with changes to other, simultaneously recorded continuous measures. In this instance, the FLM demonstrates activity shifts relative to lunar cycle, with later lunar phase (ie, a more visible moon) being associated with less early morning activity and followed by more mid-day activity. The point-wise critical value (dotted line) is the proportion of all permutation *F* values at each time point at the significance level of 0.05. When the observed *F*-statistic (solid line) is above the dotted line, it is concluded that different mean circadian activity patterns at those time points differ significantly

5 | FUTURE RESEARCH DIRECTIONS

In the future, several critical comparative questions can be targeted by human biologists seeking to understand sleep in diverse environments. Little research examining the influence of lunar phasing on human physiology has been performed and what work has been done is a hotly debated topic (Cordi et al., 2014). Work performed in mainly Western Educated Industrialized Rich Democratic (WEIRD) populations (Henrich, Heine, & Norenzayan, 2010) should be replicated outside WEIRD contexts. A few studies have explored mother-infant cosleep in small-scale societies (Crittenden et al., 2018; Mosko, Richard, & McKenna, 1997; Vitzthum et al., 2018) yet much remains unknown about the anthropology of infant and adolescent sleep (Ball et al., 2019). Additionally, cosleep is a common behavior of interest that may be shaping the sleep of adolescents and adult populations worldwide (Worthman and Melby 2002). How biological sex drives sleep in WEIRD societies similarly remains underexplored, as differences in sleep architecture as measured by EEG have not proven to be significant (Dijk, Beersma, & Bloem, 1989), but sleep research with the Himba (Prall et al., 2018) reported extremely short male sleep durations (4.78 hours vs a female average of 5.92 hours), demonstrating that socioecological contexts can evoke strong biological sex-related effects in sleep-wake regulation. Finally, there are exciting new avenues inspecting how sociality (a critical human trait) measured by way of social network analyses may be critical to illustrating how social relationships influence sleep and downstream health and wellness (Li, Kawachi, Buxton, Haneuse, & Onnela, 2019).

6 | CONCLUSIONS

Although the function of sleep remains enigmatic, research continues to reveal a fascinating, interdependent relationship between the kind of sleep we experience and our ability to learn, feel, emote, and heal (Logan & Sarkar, 2012; Nishida et al., 2009; Simon & Walker, 2018; Walker, 2009). In large-brained mammals, sleep is an emergent property of the body and brain that serves several purposes (eg, metabolic homeostasis, energy restoration and conservation, immunocompetence) and importantly for humans, sleep affects neural processing and ontogenesis that is linked with memory consolidation and emotional regulation (McNamara, Barton, & Nunn, 2010; Walker, 2009; Xie et al., 2013). Critically, for all life forms that demonstrate sleep expression, one key function of sleep is the clearance of reactive oxygen species (ROS) that lead to oxidative stress, and lack of sleep would lead to ROS accumulation and ultimately death (Vaccaro et al., 2020). Sleep has been an active target of natural selection in humans (Nunn & Samson, 2018) and mainly driven by ecological trade-offs between being vulnerable when in a different, less reactive state of consciousness and the functional fitness–enhancing benefits to the sleeper. There are few behaviors more important to our species' survival—and more worthy of scientific investigation—than sleep.

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AUTHOR CONTRIBUTIONS

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