How Environmental Factors Affect Sleep Patterns in the Adolescent BaYaka Population

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Introduction

Background

Sleep has been extensively studied, often within a universal framework that suggests a “magic number” of hours needed for optimal rest. The general consensus is that eight hours of sleep is ideal. However, such studies frequently lack a cross-cultural perspective, particularly regarding sleep behaviors in marginalized and non-industrial societies. To truly understand the complexity and variability of sleep across different cultures, it is essential to consider diverse societal contexts. Various external factors influence sleep-wake regulation, including social environment, light exposure, exercise, temperature, and dietary intake (Garcia-Garcia, 1999; Potter et al., 2016). Researchers have attempted to study sleep-wake regulation in non-industrial groups by simulating hunter-gatherer, horticulturist, and agriculturalist societies in controlled lab settings through environmental manipulation (Samson et al., 2017b). This approach facilitates the use of polysomnography (PSG) systems, the gold standard for measuring sleep. While PSGs provide valuable insights, they cannot fully replicate a person’s experience within their socio-cultural and ecological environment.

Emerging studies on the sleep patterns of subsistence societies, though limited, have identified notable trends. One key finding is that these societies generally exhibit shorter sleep durations compared to post-industrial societies (Killius et al., 2021; Prail et al., 2018; Samson et al., 2017b; Yetish et al., 2015). This is surprising given the assumption that the absence of artificial light and the structured demands of post-industrial societies, such as school and work, would result in longer sleep durations in hunter-gatherer and horticultural regions. However, exceptions exist (Smit et al., 2019). For instance, a study by Killius et al. (2021) on the same population as our study found that BaYaka sleep is generally fragmented, inefficient, and short in duration. Additionally, they observed that women in the forest BaYaka population exhibited better sleep quality and longer durations.

A significant finding in many of these studies is the plasticity of sleep from one night to the next, influenced by factors such as humidity, temperature, and moon phases (Killius et al., 2021; Samson et al., 2017a). Environmental factors impact societies differently, even when structural similarities exist. For example, while the moon phase may significantly affect sleep in one population, it may not have the same impact on another.

The Present Study

The influence of environmental factors on sleep has been extensively studied in post-industrial societies. While some research on the BaYaka has explored aspects such as social learning, physical health, familial relations, and activity within hunter-gatherer contexts, there is a notable gap in studies examining the sleep patterns of BaYaka adolescents and the environmental factors influencing these patterns. Limited research has focused on environmental factors in hunter-gatherer and forager societies, and even fewer studies have targeted adolescent populations, which are already underrepresented in sleep research. Therefore, the objective of our study is to investigate how environmental factors influence sleep patterns in the adolescent BaYaka population, a forager society in the Republic of Congo. The BaYaka are unique in their seasonal shifts from villages to forest camps for food collection. This shift results in different housing structure, socialization, and noise exposure (Killius et al., 2021). Our study aims to compare our findings with previous studies on the adult BaYaka population to identify differences in sleep quotas between age groups.

Based on previous studies and a comprehensive summary by Samson (2020), there is literature on meteorological variables and their effects on sleep. Here, we focus on seven of these variables. For example, previous studies have found that an increased ambient noise will decrease sleep duration (Samson, 2020). Samson (2020) also reports that higher temperature will result in longer sleep durations. Furthermore, when cloud cover of the atmosphere increases in the night, Minor and colleagues (2022) have found that sleep duration increases. Other studies have found that rainfall is typically a negative predictor for sleep (Samson, 2020). The same author also provides evidence that humidity can also impact circadian rhythms. Lastly, moon phase has been found to impact sleep-wake regulation in forager societies (see Samson et al., 2018).

Given the aforementioned literature on sleep, we hypothesize that BaYaka adolescents' sleep duration will be driven by the following meteorological variables: wind speed, cloud cover, heat index, precipitation, location, moon phase, and dew point. Specifically, we predict that higher wind speeds and dew points will decrease sleep duration. Furthermore, we hypothesize that a higher heat index and cloud cover will increase sleep duration. In regards to moon phases, we believe that as the phases approach the new moon, sleep duration will increase. For our last predictor, location, we predict that sleep duration will increase when in the forest compared to the village.

Methodology

For descriptions of the study site, detailed information can be found in Killius et al. (2021)'s paper. We have adolescents from both the village and forest settings, and will be comparing their sleep performances. Data collection occurred in two field seasons, however, due to the unavailability of the 2024 season data, the 2023 season data was used for this study. Our participants' ages ranged from eleven to seventeen years old.

Sleep Quotas

The methodology for this study is adapted from Killius et al. (2021). We used MotionWatch 8 devices to collect actigraphy data during the summer of 2023, focusing on sleep, nap, and activity variables. MotionWatches record light and activity data, which are used to determine sleep-wake periods. Initially, we collected data from 71 participants. However, due to corrupt or unusable data from inconsistent watch use, we excluded some participants, resulting in a final sample size of 57 for most sleep variables, 40 for 24-hour total sleep time and nap duration, and 67 for daytime activity analysis. We used Mode 1 for recording, which measures activity in one-minute epochs.

Using the sleep data, we report on the following variables:

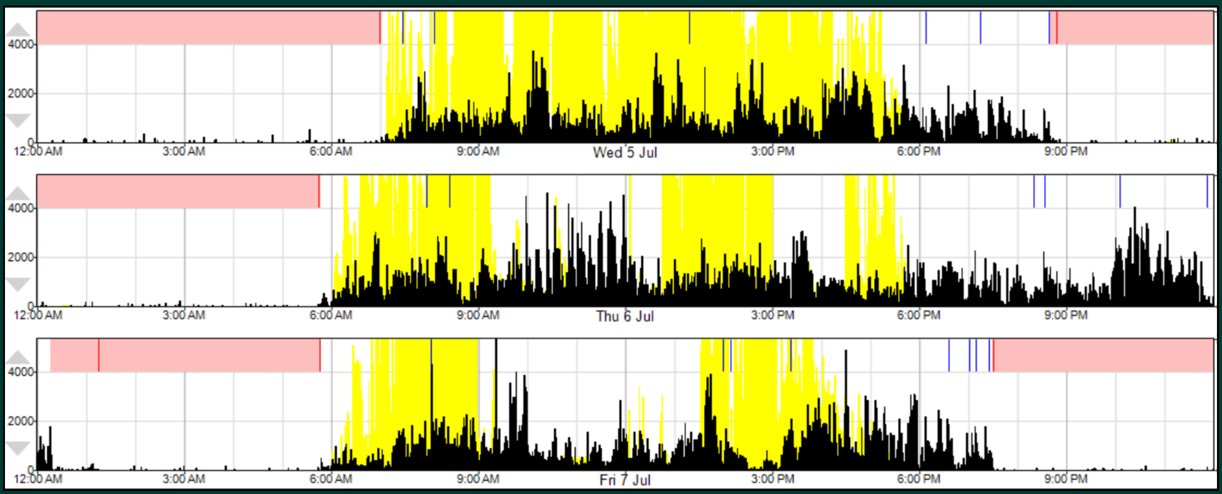
- Sleep onset: The average time it takes for the children to fall asleep
- Sleep end: The average time it takes for the children to wake up
- Time in bed: The average time children are in bed, and are assumed to have turned the "lights out". Also commonly referred to as *assumed sleep*
- Wake after sleep onset (WASO): The average time spent awake after first falling asleep
- Total sleep time (TST): The average time children are sleeping, marked between the time of when they fell asleep and when they woke up
- Sleep efficiency: The percentage of uninterrupted quality sleep, characterized by minimal activity levels throughout the sleep period
- Sleep fragmentation: Opposite to sleep efficiency, the fragmentation index indicates how frequent sleep is disrupted, marked by excessive movement throughout the night
- Twenty-four hour total sleep time (TTST): The average time children are sleeping throughout the day

- Nap duration: The average time children are napping throughout the day, which is obtained by subtracting TST from TTST

Data analysis was conducted using Microsoft Excel, RStudio, and Python. In addition to generating fixed effect plots, we also conduct quality checks in the form of Q-Q plots and residuals versus fitted plots.

Data Cleaning

The Congo data was extracted from the actigraphy and processed in CamNtech's software: MotionWare. MotionWare uses activity levels in units of counts per a specified interval in order to determine wake-sleep patterns. This is typically used for scoring sleep and nap periods after determining certain thresholds of fragmentation and activity levels. However, MotionWare has not yet been able to identify sleep periods accurately, thus, all the scoring was done manually. For sleep periods, see *sleep analysis inclusion criteria*. Below is an example showing how a scored file looks like, with the red representing scored sleep periods, the lines showing activity levels, and the yellow indicating light exposure.



Sleep Analysis Inclusion Criteria

Participants must have worn the watches for a minimum of three consecutive nights in order to be considered for analysis. Light data, which was inconsistent with the collection, was excluded from the analysis since the MotionWatch sensors detecting light were sometimes obstructed by the children's sleeves. There were distinctions in identifying and calculating total sleep time (TST) and twenty-four hour total sleep time (TTST). For an analysis of TTST, there must have been a full 24 hours of data in order for it to be utilized. Sometimes participants did not wear their watches, and in such instances, the data would be marked as missing in the software.

A total of 224 nights were analyzed (village = 90 nights, forest = 134 nights, range = 3-6 days per participant, and for TTST, a subset of 167 nights were included.

Naptime Analysis

Currently, there is no standardized method for scoring naps in actigraphy or programming software. To improve accuracy, we modified the scoring method. MotionWare 1.4.25 automatically scores nap periods, but often fails to collate detected periods into a single nap period, leading to erroneous detections. Therefore, some nap periods were initially scored by the software and then manually adjusted by inputting the number of minutes of a nap taken each hour into the spreadsheet table output for naptime periods provided by MotionWare. Averages, sums, minimums, and maximums for naptime periods were calculated manually after altering the MotionWare output. Additionally, MotionWare recorded cleaned data as zero for nap periods, rather than designating an “n/a” for days with no data collection. Each nap table was manually reviewed to ensure only existing data was included.

Physical Activity Analysis

To measure physical activity in children, we adjusted the calibration thresholds to account for differences in sedentary, moderate, and vigorous activity compared to adults. Hsuan-Ping (2017) developed cut-off points for children, summarized as follows: vigorous activity ≥ 1719 counts per minute, moderate activity ≥ 743 counts per minute, and sedentary activity ≤ 64 counts per minute. Note that these values are double Hsuan-Ping’s findings, as they represent counts per minute, whereas previous literature records counts per 30-second intervals.

The MotionWare bulk export feature was utilized for daytime analysis. According to Hinkley et al., (2012), a recording time of 3.3 to 3.4 days were required to reach a reliability estimate of 0.7 when using eight hours of activity data per day. When doing a reliability estimate for our participants’ data, we calculated the Cronbach’s alpha after setting the minimum activity data for eight hours, with exclusions if there was no movement for 60 minutes. The thresholds were set such that at least eight hours of physical activity were required to be included in the analysis, and sleep periods were excluded. Additionally, we used a standard threshold such that inactivity for 60 minutes constituted excluded data. This was analyzed after the files were cleaned for sleep analysis so that the software excluded sleep periods from daytime activity analysis.

Environmental Data

Average weather, temperature, rainfall, and humidity forecast data were obtained from WorldWeatherOnline using the exact coordinates of the village (latitude 17.50, longitude 2.48). Hourly data from 9 PM to 6 AM were averaged to compare the following variables with sleep times: average nighttime precipitation (mm), average nighttime heat index (temperature combined with humidity), average dew point (°C), and average nighttime wind speed (km/h). Moon phases were included as a cyclical element by applying the cosine function to the moon phases, starting at the new moon (+1), decreasing to -1 at the full moon, and returning to +1 at the new moon, representing all eight moon phases.

Using the aforementioned environmental variables, we incorporated them into our linear mixed-effects model as predictors for the sleep quotas. The current equation can be modeled as:

$$Sleep\ quota \sim wind\ speed\ + heat\ index + precipitation + cloud\ cover + location + dew\ point + cos(moonphase) + \ (1|subject|)$$

The expression of the moon cycle as a cosine function allows us to examine the effects of the moon phases cyclically, where the reference point is the new moon phase (starting at $cos(0°)$). Therefore, for the purposes of interpreting the fixed effects model, a positive value indicates that the sleep quotas are positively affected as the moon phases approach the new moon, and vice-versa when approaching the full moon. Here, we use ChatGPT to help incorporate this predictor as a cyclical element into the code generating the fixed effect plot. Originally, ChatGPT had suggested to represent half of the cycle as a function of sine and the remaining half as a function of cosine, however, we decided to assign angles for each phase and then ChatGPT used that information to generate a code converting the moonphase predictor as a function of cosine. The angles are assigned as follows: New Moon = 0, Waxing Crescent = 45, First Quarter = 90, Waxing Gibbous = 135, Full Moon = 180, Waning Gibbous = 225, Last Quarter = 270, Waning Crescent = 315.

Furthermore, our rationale for including the heat index instead of the individual predictors of temperature and humidity is based on initial tests of the model with separate predictors, which revealed a multicollinearity value greater than 10, raising concerns about the reliability of the model's results. To account for humidity, we use dew point as a predictor, which fits well with the model and results in low multicollinearity with other predictors. Finally, to validate the assumptions of our linear mixed-effects model, we examined several diagnostic plots. The model fit was tested by generating a Q-Q plot as well as a residuals versus fitted values plot.

Results

Descriptive Sleep Characteristics

Descriptive sleep characteristics are summarized in Table 1, with different sample sizes depending on if naps were included or not. The chosen sleep descriptives were adapted from the results of Killius et al. 2021's results. As a side note, any missing 24-hour time could not be included in the TTST analysis, but was included in the TST analysis, which explains the different participant counts.

Table 1: Overall descriptive sleep quotas (n=57) and nap/TTST quotas (n=40) of the BaYaka from actigraphic analysis conducted during the first season.

Sleep onset	21:05 (1:07)
Sleep end	5:59 (0:26)
Time in bed (h)	8.72 (0.96)
Total sleep time (h)	6.86 (0.97)
Wake after sleep onset (h)	1.59 (0.46)
Sleep efficiency (%)	78.81 (5.44)
Sleep fragmentation	33.31 (9.16)
Twenty-four hour total sleep time (h)	7.83 (1.78)

Nap period duration (h)	0.85 (1.01)

The results show that sleep onset on average occurs at 21:05 (standard deviation = 1:07), while the average sleep end occurs at 5:59 (SD = 0:26). The time spent in bed is 8.72 h (SD = 0.96), while the average TST is 6.86 h (SD = 0.97) and the TTST is 7.83 (SD = 1.78). Wake after sleep onset is found to be 1.59 (SD = 0.46). Sleep efficiency is reported as 78.81% (SD = 5.44), while the fragmentation index is 33.31 (SD = 9.16). Lastly, we report on nap duration, which is found to be 0.85 h (SD = 1.01).

Linear Mixed-Effects Model

Figures 1 and 2 show the results of the data quality checks conducted for the model fit.

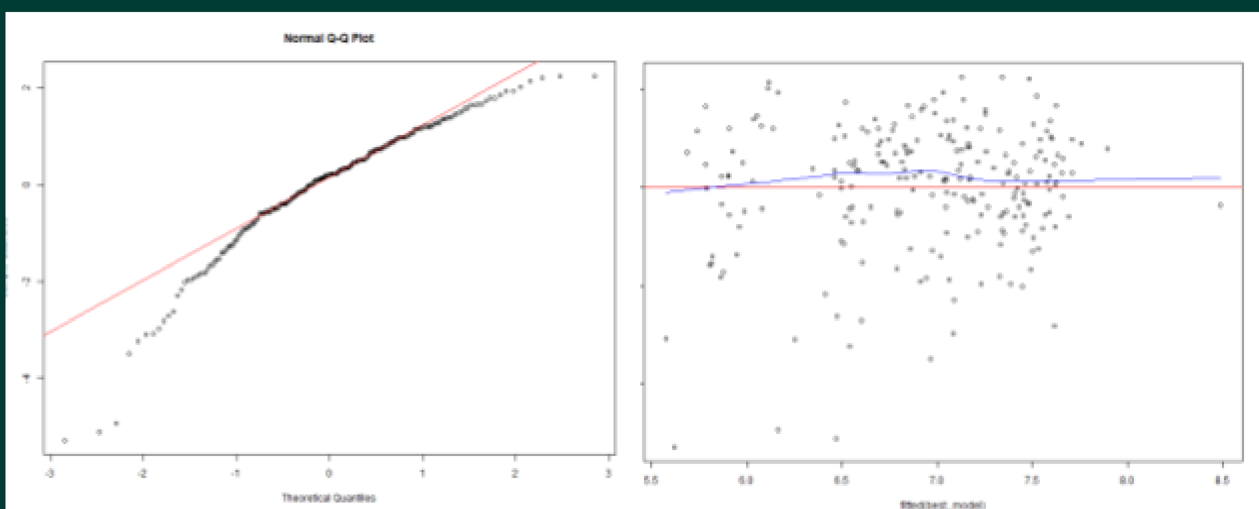


Figure 1: Q-Q plot showing the normal distribution and a residuals versus fitted plot for TST. For the Q-Q plot, a good model fit is identified by the plotted values as close to the theoretical line (shown in red). There is some deviation along the tails, but overall, this demonstrates a good fit. The residuals versus fitted values plot shows a scattered distribution of the residuals around zero, with no distinct patterns or trends, indicating that the assumptions of linearity are reasonably met.

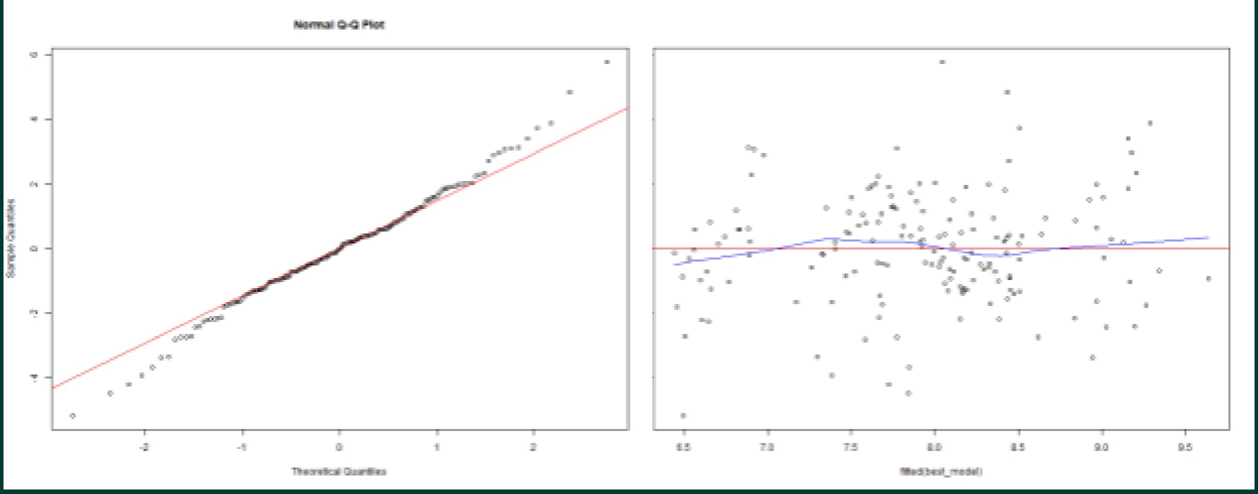


Figure 2: Q-Q plot showing the normal distribution and a residuals versus fitted plot for TTST. For the Q-Q plot, a good model fit is identified by the plotted values as close to the theoretical line (shown in red). There is again some deviation at the tails, but overall, these plots represent a good fit of the model.

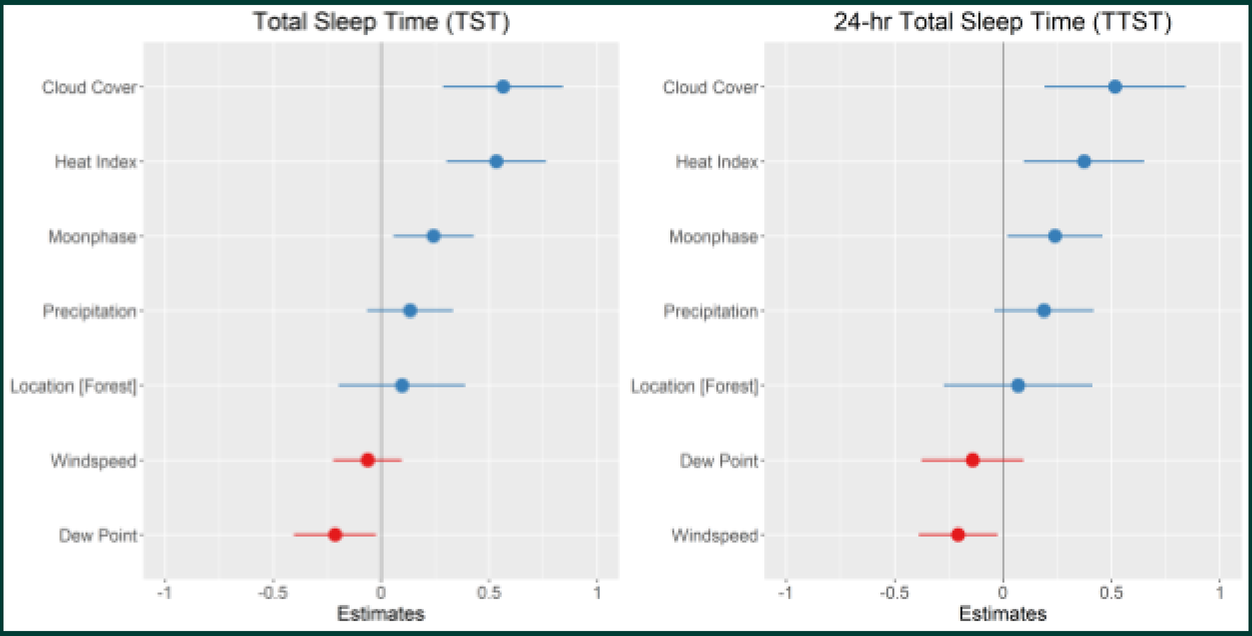


Figure 3: A fixed-effects plot showing how the predictors impact both TST (n=57) and TTST (n=40) on adolescent sleep. The reference variable for moonphase is set as the new moon. Predictors that have a positive effect on both response variables are represented by blue, while negative effect predictors are denoted by red. The lines represent the 95% confidence intervals. Results for TST indicate that heat index and cloud cover are significantly positive predictors for total sleep time, while moonphase is a moderately positive predictor (meaning the closer the phase is to the new moon, the higher the total sleep time). We also find that dew point is a moderately negative predictor of TST. For TTST, we similarly find that cloud cover and heat index are significantly positive predictors, respectively.

We report the results obtained from our linear mixed-effects models, where ß is the estimate, SE is the standard error, and CI is the 95% confidence interval. The models revealed that cloud cover is a strong positive predictor for TST (ß + SE = 0.05 + 0.01, $p < 0.001$, CI = [0.02, 0.07]) and TTST (ß + SE = 0.05 + 0.02, $p < 0.01$, CI = [0.02, 0.09]). Similarly, the heat index is a significant positive predictor for TST (ß + SE = 0.84 + 0.18, $p < 0.001$, CI = [0.48, 1.41]) and TTST (ß + SE = 0.75 + 0.28, $p < 0.01$, CI = [0.19, 1.30]). The moon phase is also a positive predictor for TST (ß + SE = 0.57 + 0.22, $p < 0.05$, CI = [0.13, 1.00]) and TTST (ß + SE = 0.77 + 0.36, $p < 0.05$, CI = [0.06, 1.47]). For TST, the dew point is a negative predictor (ß + SE = -0.57 + 0.26, $p < 0.05$, CI = [-1.08, -0.06]), while wind speed is a negative predictor for TTST (ß + SE = -0.58 + 0.26, $p < 0.05$, CI = [-1.10, -0.07]). See Figure 3 for the fixed effect plots.

Physical Activity

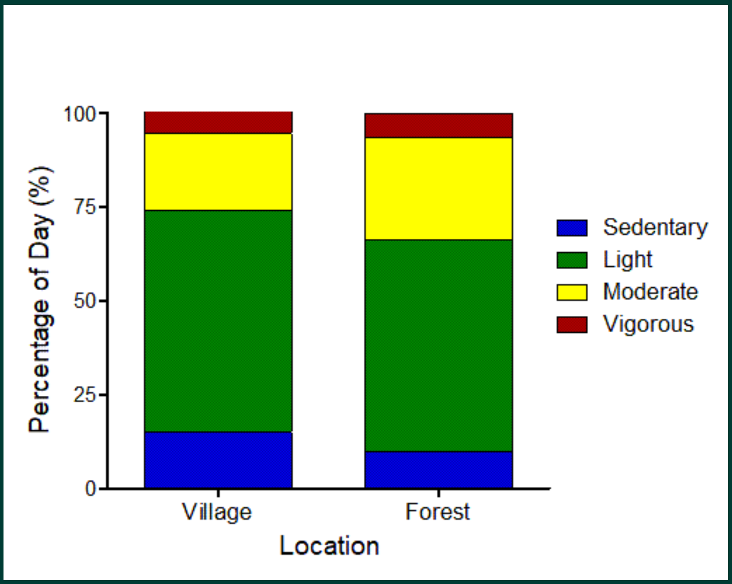


Figure 4: A comparison between the village and forest BaYaka adolescent's activity levels, ranging from sedentary, light, moderate, and vigorous activity. The sample size for the population was n = 67 and 242 days of data (village = 112, forest = 130). Results indicate minor activity level differences between the groups, but nothing statistically significant.

We additionally report on the activity level descriptive statistics. Our reliability estimate is calculated to be $\alpha = 0.88$. Regarding the breakdown of activity levels through the day, the village-residing adolescents are on average sedentary for 15.03% (SD = 10.99) of the day, have low activity 59.14% (SD = 8.40) of the time, moderately moving 20.48% (SD = 9.34) of the day, and vigorous for 5.36% (SD = 4.49) of the day. For adolescents in the forest, we report the following: 10% (SD = 8.56) sedentary, 56.25% (SD = 9.08) light activity, 27.30% (SD = 10.14) moderate, and 6.45% (SD = 4.02) vigorous. The calculated moderate-to-vigorous physical activity (MVPA) for the village is 25.84% (SD = 11.82) and the forest is 33.75% (12.66). The overall MVPA for all adolescents is 30.09% (SD = 12.88).

Discussion

Descriptive Sleep Quotas

The goal of our study was to examine sleep patterns in the adolescent BaYaka population, who move between two socio-ecological locations because of their subsistence lifestyle as foragers. Our findings for the sleep descriptive statistics are in-line with other studies focusing on small-scale hunter-gatherer societies, which reported lower sleep duration, higher sleep fragmentation, and lower sleep efficiency than post-industrial societies. In comparison to the adult BaYaka population as studied by Killius and colleagues (2021), sleep duration is much higher, fragmentation is significantly lower, and sleep efficiency is higher as well, suggesting that adolescents obtain better quality sleep. Although, sleep onset and sleep end are very similar to the adult BaYaka participants, with the adolescents having a slightly prolonged sleep end.

Nap duration was shorter compared to previous studies on BaYaka sleep targeting adults (Killius et al., 2021). This may correlate with the longer sleep end time in the children and the increased sleep efficiency, resulting in decreased nap durations. Future studies should investigate sleep patterns of young adults to determine the approximate age in which sleep quality decreases. The significantly decreased wake after sleep onset in adolescents versus adults also accounts for the increased sleep duration, resulting in children likely not needing more naps throughout the day. Health implications of the BaYaka's sleep quality should also be investigated. Benkirane (2022) found that sleep fragmentation directly impacted sleep efficiency, the number of REM phases, and the proportion of time spent in N3 and REM. The authors also found that behavioural inhibition would decline after experiencing chronic sleep fragmentation. Thermal stress may also be associated with low sleep quality, as BaYaka domiciles do not contain doors (Killius et al., 2021). Overall, there are many health risks associated with similar low quality sleep in post-industrial societies that can translate into the BaYaka population.

Environmental Predictors for Sleep

Overall, our hypotheses for cloud cover, heat index, wind speed, dew point, and moon phase are supported by the linear mixed-effects models. However, while dew point is a negative predictor for TST, it is not a significant predictor in TTST, meaning that a decrease in dew point increases nighttime sleep duration. Dew point is proportional to humidity, which explains the negative correlation between dew point and sleep duration, given that the recommended humidity should be no more than 60%. Given our findings for dew point, this may suggest that the nighttime environment may be too moist for longer sleep durations.

Cloud cover and heat index are correlated with each other in that the higher the cloud cover percentage in the nighttime, the more heat is trapped in the atmosphere, thus, reflecting how hot the body perceives the nighttime air (Rokonuzzaman, 2017). Heat index will tend to increase as cloud cover increases, a phenomenon that occurs during the nighttime as reported by Rokonuzzaman and colleagues. This also correlates with the findings of Samson (2017a), where temperature—which is proportional to heat index—is a positive predictor of sleep duration. The important distinction to make is that while heat index is a positive predictor of TST and TTST, that is because heat index is the temperature perceived by the human body after accounting for humidity. This establishes that the dew point is not representative in this observation. In addition, the moon phase findings are in line with what Samson and colleagues (2018) found in the Hadza population. The Hadza lead a similar lifestyle as the BaYaka as hunter-gatherers. Both of these small-scale societies utilize minimal artificial light, which may explain the similar findings. Moreover, these results are also consistent with studies conducted in post-industrial societies (Cajochen, 2013).

Our findings reveal that precipitation and location are not significant environmental predictors of sleep duration, and thus, these results do not support H1. The results for precipitation can likely be explained by the lack of variation in precipitation over the study period, as most nights there were rarely any forms of precipitation. As for location, similar results were observed in Killius and colleagues' findings. Location was not a significant predictor for the adult BaYaka population, and the same follows through with the adolescents. We hypothesized that since villages had noisier environments than forests, forests would result in longer sleep duration. However, a study by Arregi et al. (2022) revealed no significant effect of environmental noise on any sleep quotas in adolescents living in rural areas. The authors of this study reference Lee and colleagues' (2021) study that found no correlation between sleep disruption and traffic noise at 65 decibels (dB).

Lastly, we found that wind speed was a negative predictor, as originally hypothesized. Our rationale for this hypothesis stems from wind speed producing ambient noise. In both the village domiciles and forest camps, the housing structure makes noise a likely disruption during sleep. Although previous research has revealed that children are less easily awoken by ambient noise (Lee et al., 2021), there are reasons exclusive to forager populations which may account for why noise contributed by wind speed may disrupt sleep. Samson's (2015) sleep intensity hypothesis explains that selective pressures such as predation risk in their environments requires humans to fulfill their sleep in a short allocated time. While this hypothesis applies to all humans, it is most applicable to individuals with more exposure to predation risks, which would be the case for BaYaka children versus children in industrialized societies due to the domicile and forest camp structures. Since wind speed was a negative predictor only for TTST, we assume that naps were profoundly impacted by wind speed. This makes sense as naps are more prone to disruption than a sleep period at night since naps only go so far as lighter sleeping stages (Gartenberg, 2023).

Physical Activity

Although our physical activity findings are preliminary, we found that the MVPA percentage of BaYaka children is extremely high compared to findings in post-industrial societies (Salway et al., 2023). Recently, Kretschmer and colleagues (2023) working with BaYaka children found that BaYaka children exceed the physical activity WHO recommendations by three times. Our findings are in line with theirs. Although we have not compared physical activity to sleep in this study, we would like to examine the relationship between the two variables, especially considering that previous studies have reported high levels of activity throughout the day translate to longer and more efficient sleep (Matricciani, 2024).

Limitations and Future Directions

While the models have demonstrated notable patterns of the predictors on the sleep response variables, some missing data has hindered the optimization of the model. Our current linear mixed-effects model lacks other important biological and environmental considerations, namely sex and age. Due to our incomplete dataset, we have not yet been able to incorporate these elements. Additionally, our model fit would be optimized with the presence of a polynomial term, which is currently not included. In the future, we would like to see how age*location would work in the model, as has been tested by Killius and colleagues (2021). Moreover, given the incomplete activity data, we have not been able to examine correlations between activity levels and other sleep quotas, something we aim to do in the future.

Additionally, while our model equations work great for TST and TTST, they did not suffice for two other sleep quotas which we aimed to report on as response variables in the fixed-effects plots: sleep fragmentation and sleep efficiency. The current model needs to be revamped in order for the predictors to be as consistent as they can be amongst all the sleep quotas. Future work would entail incorporating Bayesian statistics to help determine model fit. Moreover, our moon phase results, we do not take cloud cover into consideration, which may impact the results slightly in regards to the moon's lux impacting sleep in the BaYaka population. Going forward, we would like to explore the moon and cloud cover relationship and how it can be modeled as a single predictor.

Conclusion

Our study's results indicate that there are a handful of environmental factors at play influencing sleep in the adolescent BaYaka population. We found evidence for five predictors having a significant effect on total sleep time and 24-hour total sleep time, with three predictors overlapping between the response variables. In addition to this, we found that dew point impacts nightly sleep duration, but not sleep duration across 24 hours. Contrastingly, wind speed negatively influences TTST but does not affect TST, which goes against our hypothesis. Surprisingly, we find that neither location nor precipitation have a significant effect on the sleep quotas. In the future, we would like to improve our model to examine how the predictors impact sleep efficiency and sleep fragmentation, as well as how extremely high physical activity of BaYaka children influences sleep variables.

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