Feasibility of Collecting Time-Resolved Radio Frequency and Sleep Measures in a Cohort of Firefighters

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Abstract

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Background:

Firefighters encounter serious occupational risks from burns, smoke inhalation, heat exhaustion, physical and mental stress, and higher incidence of cancer. The National Institute for Occupational Safety and Health (NIOSH) recently released two studies finding that firefighters' cancer diagnoses are 9% above those of the general public and their cancer-related deaths are 14% greater than the general public (National Fire Protection Association, 2022).

Many fire stations are located in populated central areas with close proximity to cell towers, which are a source of radio frequency-electromagnetic field (RF-EMF) exposure. Moreover, firefighters often are equipped with two-way communication radios and these

devices are an additional source of RF exposure. A typical frequency used by fire department radio systems is 154 MHz (*IAFF*, 2008)

Currently, the FCC has limits on RF exposure, and the International Commission on Non-Ionizing Radiation Protection has also published recommended exposure limits known as the ICNIRP (ICNIRP, 2010) limits. These limits are based on levels of radio frequency exposure found to cause tissue heating. It is possible that RF exposure below levels that cause tissue heating and tissue damage may cause detrimental health outcomes outside of tissue heating. In 2011, the International Agency for Research on Cancer (IARC) categorized RF as a possible human carcinogen (group 2B) (IARC, 2011). This was based on an increased risk for glioma, a malignant type of brain cancer associated with wireless phone use. Studies have also suggested that RF exposure may affect heart rate variability and sleep quality. (Misek et al., 2018)

With the support of the IAFF (International Association of Fire Fighters), this project will measure RF exposure among firefighters in the Puget Sound area and will also analyze their sleep quality data through a validated survey distributed to fire stations in this geographical sampling. The goal of this pilot project is to test the feasibility of a larger scale research project.

Methods:

Participating fire services included the Seattle Fire Department, Central Pierce Fire and Rescue, Puget Sound Regional Fire Authority, and the Renton Regional Fire Authority. Three of these fire districts were participating from the beginning, and one joined the study partway through. The stations sampled went through a rigorous selection process that was conducted in the programming language "R," which weighed both their EPA land use classification, as well as their reported number of proximal cell towers. These fire stations had a range of urbanicity as well as a range of proximal cell towers. Once selected, GPS-logged outdoor radio frequency samples were taken. These samples were taken with an omnidirectional antenna and with a directional antenna.

Indoor RF samples were taken at 10 of the stations that were monitored for outdoor RF exposure. Because of Covid-19 health concerns, indoor samples were not collected from fire service B. These samples were taken overnight to capture a larger data set. After walking through the fire station, the sampling equipment was placed in an area with measurable RF exposure to collect RF data for either 24 or 72 hours.

To analyze these RF monitoring samples, the programming language "R" was again used. The data files were initially imported with a custom "R" function that did various data cleaning processes described in this paper (Grolemund & Wickham, 2011; Wickham, 2011, 2011, 2016; Wickham et al., 2022). The samples were run through another custom function that subset the data to the appropriate frequency range and output:

1. A plot showing the 95th quantile of RF intensity at 0.5mHz intervals
2. An Excel file with the 20 frequencies with highest RF intensities
3. An Excel file detailing the percentage of the INCIRP occupational limit the 95th quantile RF intensities are at

After this, a sleep survey was sent to the initial three participating fire services as well as the fourth fire service that joined the study at this point through Redcap. This survey was a modified Pittsburgh Sleep Quality Index survey. The Pittsburgh Sleep

Quality Index (PSQI) is an effective instrument used to measure the quality and patterns of sleep in adults.. Our survey was modified to adjust for shift work. We then scored the survey responses based on the PSQI scoring system.

Results:

We were able to identify the largest contributing frequencies to RF exposure. These frequencies were around 480 MHz, and 5.8 GHz for the outdoor omnidirectional antenna samples. The highest contributing frequencies for the outdoor directional antenna samples were around 750 MHz, 1.95 GHz, 5.8 GHz, and 8.5 GHz-9 GHz. The highest contributing frequencies for the indoor omnidirectional antenna samples were from 320 MHz-400 MHZ, and 5.8 GHz-5.81 GHz.

Radio frequency exposures at all stations surveyed were below 1% of the ICNIRP occupational guideline for both outdoor and indoor samples. Our outdoor omnidirectional RF samples ranged from 0.05% to 0.37% of the ICNIRP occupational guideline. Our outdoor directional RF samples ranged from 0.05% to 0.31% of the ICNIRP occupational guideline. Our indoor overnight omnidirectional antenna samples ranged from 0.10% to 0.35% % of the ICNIRP occupational guideline.

Results from our PSQI survey responses indicated that 102 (71%) of our respondents were classified as poor sleepers (PSQI score >= 5). In addition, another metric used to evaluate sleep, short sleep duration, revealed that 53 (37%) of our respondents reported that on average while not on shift, they have short sleep duration.

Conclusions:

Results from the outdoor and indoor fire station RF sampling provided a varied range of exposures both between fire stations and within indoor and outdoor samples at any given fire station. This indicates that we were able to collect very low intensity RF exposures at the fire stations. This represents a novel method of sampling for RF exposure that could be used for a larger scale study on RF exposure and potential health outcomes. Results from the outdoor and indoor fire station RF sampling indicate that firefighters employed at the sampled stations are not at risk of tissue heating from RF exposure.

We theorize that among the frequencies contributing the most to RF exposure, frequencies between 320 MHZ and 750 MHz correspond to emergency response communication systems, frequencies around 5.8 GHz are attributable to Wi-fi, and frequencies from 8-9 GHz are attributable to cellular phone service providers. (*US Department of Transportation*, 2017)

Participating firefighters who answered the PSQI sleep survey do not have a significantly different proportion of individuals with short sleep duration (37%) than other protective service occupations in the U.S. (38.2%) (Luckhaupt et al., 2010a). We did not find a significant relationship between RF exposure at a fire station and increased PSQI scores in respondents from that fire station. This might be because a relationship between the two variables does not exist, or it might be because our sample size was too small.

Acknowledgements

This research study was funded by the International Association of Fire Fighters. My master's degree was funded by the National Institute for Occupational Safety and Health through their education and research center. I would like to thank the Puget Sound Regional Fire Authority, the Seattle Fire Department, the Renton Regional Fire Authority, and Central Pierce Fire and Rescue for their participation and cooperation in this study. The content of this thesis is solely the responsibility of the author and does not necessarily represent the views of the University of Washington, the participating fire services, or the National Institute for Occupational Safety and Health.

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Introduction

What is Radio Frequency?

Radiation is the emission of energy from any source. Examples of sources include x-rays, the sun, and even the human body giving off heat. Radiation can be categorized as either ionizing or non-ionizing radiation. Ionizing radiation is higher energy radiation that is capable of removing an electron from an atom and damage DNA, which can lead to cancer. (American Cancer Society, 2022)

Radio frequency (RF) encapsulates the lower energy portion of the electromagnetic spectrum, below infrared radiation and visible light and is classified as non-ionizing radiation. Common sources of RF include radio waves and microwaves. In the occupational setting, cell tower maintenance workers and radar equipment maintenance workers are exposed to significant levels of RF (American Cancer Society, 2022).

Energy transmitted in non-ionizing radiation does not have enough power to remove electrons from atoms and is not capable of causing DNA damage and cancer in the same way as ionizing radiation. If RF exposures are large enough, they can cause tissue heating which leads to burns and body tissue damage. RF that is strong enough to cause tissue heating is rare, and typically occurs in industrial settings. Cell phones, handheld radios, and wireless networks also produce RF energy. A recent study has found evidence that cell phone radiated radio frequency waves were effective in increasing brain tissue temperature. (Forouharmajd et al., 2018)

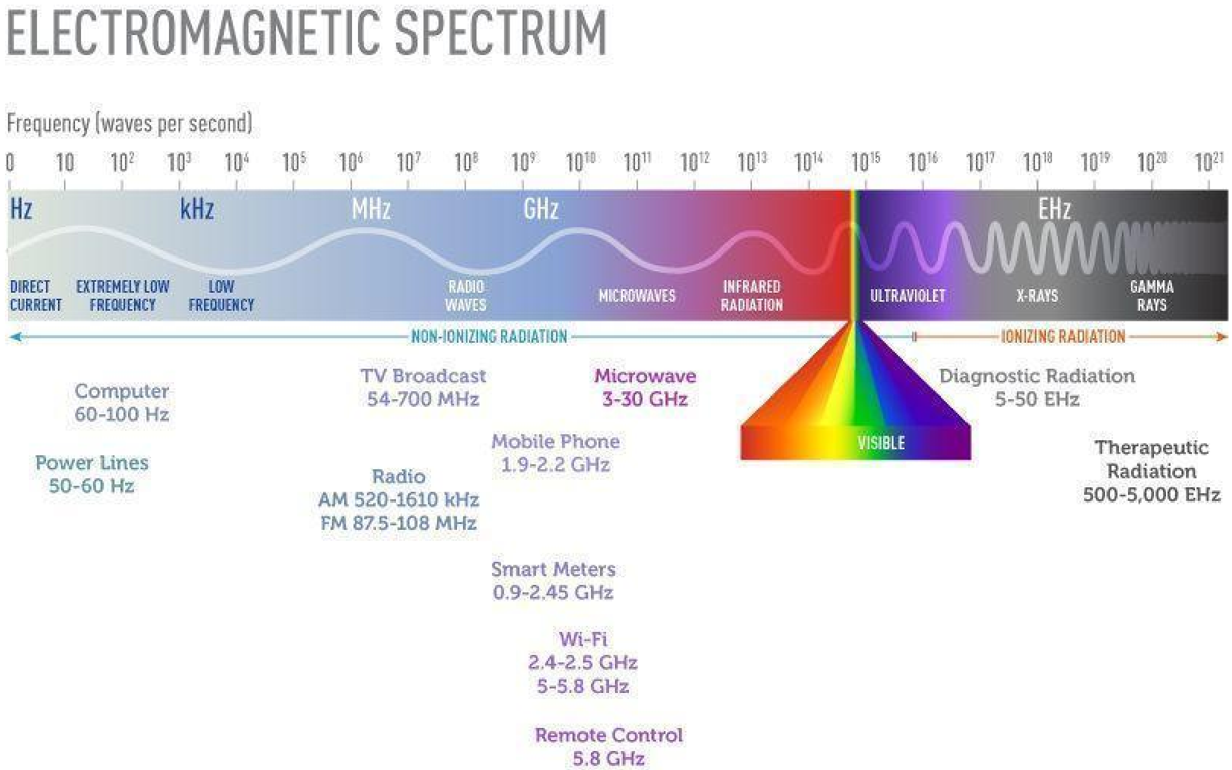

Figure 1. Electromagnetic Spectrum breakdown, Image credit: National Cancer Institute

RF and Firefighters

For our population of interest, it is suspected that handheld radios used for communication may be a source of RF exposure. In addition to this type of RF exposure, municipalities are known to have leased space for cell phone tower installation on the roofs of fire stations. This would be another source of RF exposure that firefighters would encounter at their work site. Cell phone companies maintain there is no additional risk from their cell towers, however the risk they refer to is the risk of tissue heating. There are concerns that RF exposures could have non-thermal effects on the human body at lower levels (World Health Organization, 2014.)

RF and Potential Health Outcomes

There is scientific uncertainty regarding residential exposure to extremely low-frequency magnetic fields and the possibility of an increased risk of childhood leukemia, CNS tumors, and lymphoma (Olsen et al., 1993). Some studies have identified an association between proximity to power lines and an increase in these diseases, while other studies have failed to find such an association. (Pedersen et al., 2015)

The International Association of Fire Fighters (IAFF), which funded this study, "oppose[s] the use of fire stations as base stations for towers and/or antennas for the conduction of cell phone transmissions until a study with the highest scientific merit and integrity on health effects of exposure to low-intensity RF/MW radiation is conducted and it is proven that such sitings are not hazardous to the health of our members." (IAFF webpage, Nd) This study is a pilot to determine the feasibility of collecting radio frequency exposure measurements at fire stations and measuring potential health outcomes.

There have been many controversies concerning RF-EMF exposure and its potential health outcomes. Many of the studies probing a possible connection between RF-EMF and its potential health outcomes have been focused on cancer (Morgan et al., 2015), genetic damage (J.-Y. Kim et al., 2008; Ruediger, 2009), reproductive disorders (Altun et al., 2018; Falzone et al., 2011), immune dysfunction(Kazemi et al., 2015), long term cognitive dysfunction (Jiang et al., 2016; J. H. Kim et al., 2017; Son et al., 2018), and kidney damage (Kuybulu et al., 2016; Türedi et al., 2017). However, despite the number of studies analyzing RF-EMF and its potential health outcomes, its potential biological effects have not been definitively proven. Adding to this uncertainty about RF-EMF exposures is the fact that many studies have published data on the subject that is contradictory in their outcomes.The mechanism of biological effect by RF-EMF exposure is not yet clear, and many studies have published data on the subject that is contradictory in their outcomes. Studies indicate that cellular phone RF-EMF emissions are absorbed into the brain and can affect neuronal activity (Jeong et al., 2015; Jiang et al., 2016). Studies have also suggested that this absorbed RF-EMF exposure in the brain can increase tissue temperature and affect neuronal activity (Wainwright, 2000; Wyde et al., 2018).

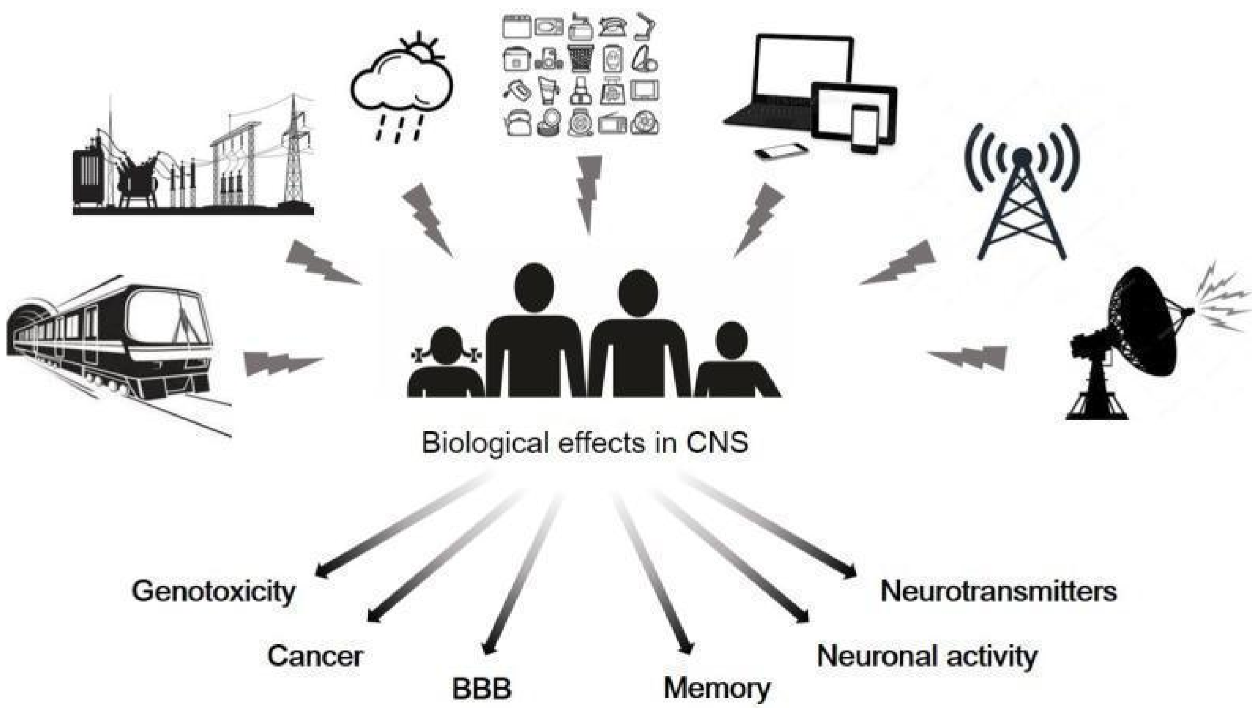

Figure 2. RF sources and potential CNS effects, reprinted from (J. H. Kim et al., 2019)

It has been hypothesized that there are potential neurological effects resulting from radio frequency- electromagnetic field (RF-EMF) exposure including headaches (Frey, 1998), changes in sleeping patterns (Danker-Hopfe et al., 2016; Wagner et al., 1998), and epilepsy (Mann et al., 1998; Schmid et al., 2012). There have also been suggestions that

RF-EMF exposure can influence changes in blood pressure (Braune et al., 1998). While these findings have been inconsistent, there have been several epidemiological studies reporting neurological cognitive disorders because of RF-EMF exposure from cell phone base towers including headaches, tremors, dizziness, memory loss, reduced concentration, and sleep disturbance. (Abdel-Rassoul et al., 2007; Hutter et al., 2006; Kolodynski & Kolodynska, 1996; Santini et al., 2002).

In 2011, the International Agency for Research on Cancer (IARC) categorized RF as a possible human carcinogen (group 2B) (IARC, 2011). This listing was based on an increased risk for glioma, a malignant brain cancer associated with wireless phone use. The National Toxicology Program (NTP) released results from a study that exposed mice to similar frequencies as used by 2G and 3G cell phones. This study found: 1) clear evidence of an association with tumors in the hearts of male rats;2) some evidence of an association with tumors in the brains of male rats, and 3) some evidence of an association with tumors in the adrenal glands of male rats. (National Toxicology Program, 2018). A follow-up study by the Ramazzini Institute produced results that reinforce these findings. Importantly, all of the exposures in the Ramazzini study were at levels below the FCC limits, which means that humans can be exposed to these levels of RF.(Falcioni et al., 2018).

Firefighters' extended shifts and long work weeks exposes them to sleep deficiency and circadian rhythm disruption. Sleep is increasingly recognized as a critical component of healthy development and overall health (Chaput et al., 2016; St-Onge et al., 2016). Long-term sleep deficiency is a concern for firefighters because of its association with morbidity and mortality. (Matricciani et al., 2012; Medicine et al., 2006). Some of the adverse health outcomes that have been associated with chronic sleep deficiency include obesity (Wu et al., 2014), hypertension (Y. Wang et al., 2015), cardiovascular disease (D. Wang et al., 2016), and type 2 diabetes (Shan et al., 2015). Inadequate sleep is also associated with daytime fatigue, daytime sleepiness, depressed mood, and poor daytime functioning. (Owens et al., 2014; Roehrs et al., 1983; Shochat et al., 2014; Wolfson & Carskadon, 1998). These symptoms can hinder firefighters in the performance of their duties.

Because of studies indicating that RF-EMF exposure could be associated with sleep disruption (Wagner et al., 1998; Danker-Hopfe et al., 2016) and the vulnerability of firefighters to sleep disruption, we elected to use sleep disruption as our health outcome of interest. Healthy sleep comprises many different metrics including adequate sleep duration, good quality, appropriate timing, and the absence of sleep disorders. We utilized the Pittsburgh Sleep Quality Index (PSQI) to evaluate sleep quality.

If RF is disrupting the autonomic nervous system and consequently disrupting sleep, we are able to theorize a possible mechanism of action for RF exposure that increases the risk of cancer. Sleep is important for many health reasons, one of which is that the body best achieves the repair double of stranded breaks in DNA during sleep. Accumulation of double stranded DNA breaks may lead to cell death and cancer. (Zada et al., 2019). Double-strand breaks (DSBs) in DNA form as a result of exposure to exogenous agents, such as radiation and certain chemicals, as well as through endogenous processes, including DNA replication and repair. (Cannan & Pederson, 2016). Thus, while non-ionizing radiation from RF might not be directly causing double-stranded DNA breaks, it could be an agent of sleep disruption and impairing the body's ability to naturally repair double- stranded breaks.

Firefighter Exposures

Firefighters are at increased risk of cardiovascular disease, pulmonary disease, cancer, and noise-induced hearing loss. Occupational medical care for firefighters needs to monitor for these long-term health risks. Firefighters typically encounter multiple exposure factors that contribute to elevated workplace stress and hazards. Physical hazards include heat exposures, physical injury, traumatic physical and physiological events during emergency call responses, fatigue, COVID-19 exposure, and RF exposure. As described above, firefighters are exposed to RF from multiple sources some of which are unique to their occupation. Firefighting chemical and biological hazards have been well documented. Firefighters are frequently exposed to combustion byproducts that contain significant concentrations of hazardous agents including carbon monoxide, benzene, sulfur dioxide, hydrogen cyanide, aldehydes, hydrogen chloride, polycyclic aromatic hydrocarbons (PAHs) and particulate matter (Brandt-Rauf et al., 1988). Many of these agents have been suspected of contributing to cardiovascular, respiratory, or neoplastic diseases among firefighters. Finally, firefighters operate in a dynamic, complex work environment, and a variety of workplace factors may contribute to elevated stress in their jobs.

Significantly, firefighters routinely encounter sleep disruption and shift work, a combination which has been recognized by IARC as a "probable" (Group 2A) carcinogen. This is based on strong mechanistic evidence in animal and emerging human epidemiological studies. (Mogavero et al., 2021; Ward et al., 2019). The IARC recently classified occupational exposure of firefighters as *carcinogenic to humans*. (Group 1)

(Demers et al., 2022). This classification was made on the basis of sufficient evidence of such cause and effect in humans. There was strong mechanistic evidence in the IARC's monographs. Occupational firefighter exposure exhibits 5 of the 10 key characteristics of carcinogens. is genotoxic, induces epigenetic alterations, induces oxidative stress, induces chronic inflammation, and modulates receptor-mediated effects.

Assessing Sleep Quality

In preparation for this study, part of the literature review included determining viable sleep monitoring tools for occupational cohorts. Objective, direct measurements of sleep with polysomnography, which assesses many parameters including limb movement, brain waves, heart rates and rhythms, allows clinicians to differentiate sleep stages and sleep quality. This is the "gold" standard for sleep quality measures. However, direct measures of sleep collected with polysomnography are costly, time consuming, and invasive. Moreover, we had concerns that stress effects would not be accurately captured by one night of sleep monitoring because those effects might be better captured over a longer period of time. Most studies use indirect sleep assessment tools because they are less expensive than direct measures. According to a review of sleep quality assessment tools published in 2021, the PSQI is "the most commonly used measure of subjective self-report sleep quality." (Fabbri et al., 2021). The PSQI was developed to quantify sleep quality and has been validated by studies that use the PSQI as a convergent validity measure. This suggests that the PSQI can be considered as an accepted reference or "gold" standard for self-perceived sleep quality. (Fabbri et al., 2021). In addition, it is the most widely used sleep health assessment tool in both clinical and non-clinical populations. (Mollayeva et al., 2016). The PSQI consists of 24 questions, or items to be rated, relating to the previous month's sleep. While the PSQI is known to have strong validity and reliability, there are concerns relating to the expansive recall time for participants. There are several other useful sleep surveys that are widely used including the Epworth sleep scale, the Jenkins sleep scale, and the mini-sleep questionnaire, but none have been validated to the extent that the PSQI has been. Because of its wide use, validity, and the known precedent of the PSQI for assessing sleep in shift workers (Thach et al., 2020; Zhang et al., 2016), we also decided to utilize the PSQI for our study.

Specific Aims

Although studies have monitored for RF exposure in high intensity settings, it is relatively novel to sample for RF exposure in low intensity settings. Our specific aims for this pilot project are:

1) Determine a systematic, informed method of selecting fire stations that will represent a broad range of RF exposures using predictors of RF variability including location (urban, suburban, rural) and proximity to cellular base stations (CBS).
2) Survey the range and frequency distribution of outdoor RF exposures at a subset of 15 fire stations in the Puget Sound area.
3) Survey the range and frequency distribution of indoor RF exposures at a subset of 10 fire stations in the Puget Sound area.
4) Distribute a validated sleep quality questionnaire to firefighters working in the 15 surveyed fire stations. Determine a cross-sectional association between RF exposure and questionnaire-based measures of sleep and stress.

Successful completion of these aims will establish the feasibility of monitoring area RF exposures among firefighters.

Methods

Fire Station Sampling Selection

We attempted to select fire stations that presented a range of RF exposure intensities. We aimed to determine if there would be measurable RF differences in these fire stations. If there were measurable differences, could we find predictors of RF exposure? One of our hypothesized predictors of fire station RF exposure is level of urban development. Conceivably, the more urban setting for a fire station, the more sources of RF exposure it will have because of increased cellular communications, electronics, and radio waves (Birks et al., 2018).

The second hypothetical predictor of RF exposure that we selected for this study was the number of proximal cell towers to the fire station. Cell towers are constantly broadcasting information via radio frequency, and we predicted that fire stations with a greater number of nearby cell towers would have higher levels or intensities of RF exposure. The number of proximal cell towers is also an important choice as a potential RF intensity predictor because the IAFF is concerned about municipalities placing cell towers near fire stations.

In order to select a set of fire stations with a range of urban development as well as a range in number of proximal cell towers, we began by plotting the fire stations in the participating fire districts in R. This data came from Homeland Infrastructure Foundation-Level Data. We transformed the shape file to have latitude and longitude, removed duplicate addresses from the address column, removed duplicate coordinates, and plotted a heatmap of U.S. fire stations (Homeland Infrastructure Foundation-Level Data, 2021) . We then utilized aggregate data from "OpenCellID" (OpenCelliD, 2021) to load in GPS locations of U.S. cell towers. We cropped this cell tower dataset to latitudes between 49 and 45, and longitudes between -121 and -123. We were then able to create a buffer with a 150-meter radius around the fire stations and report the number of cell towers within that buffer for each station. We utilized the EPA's smart location database, more specifically variable "D1D", which is gross activity density (employment + housing units) on unprotected land. This dataset classifies census blocks, the smallest geographic area for which the Bureau of the Census collects and tabulates decennial census data, as urban, suburban, or rural. Finally, we added this urbanicity data to our fire station buffer dataset and were able to see how many proximal cell towers a fire station had, as well as its level of urbanicity.

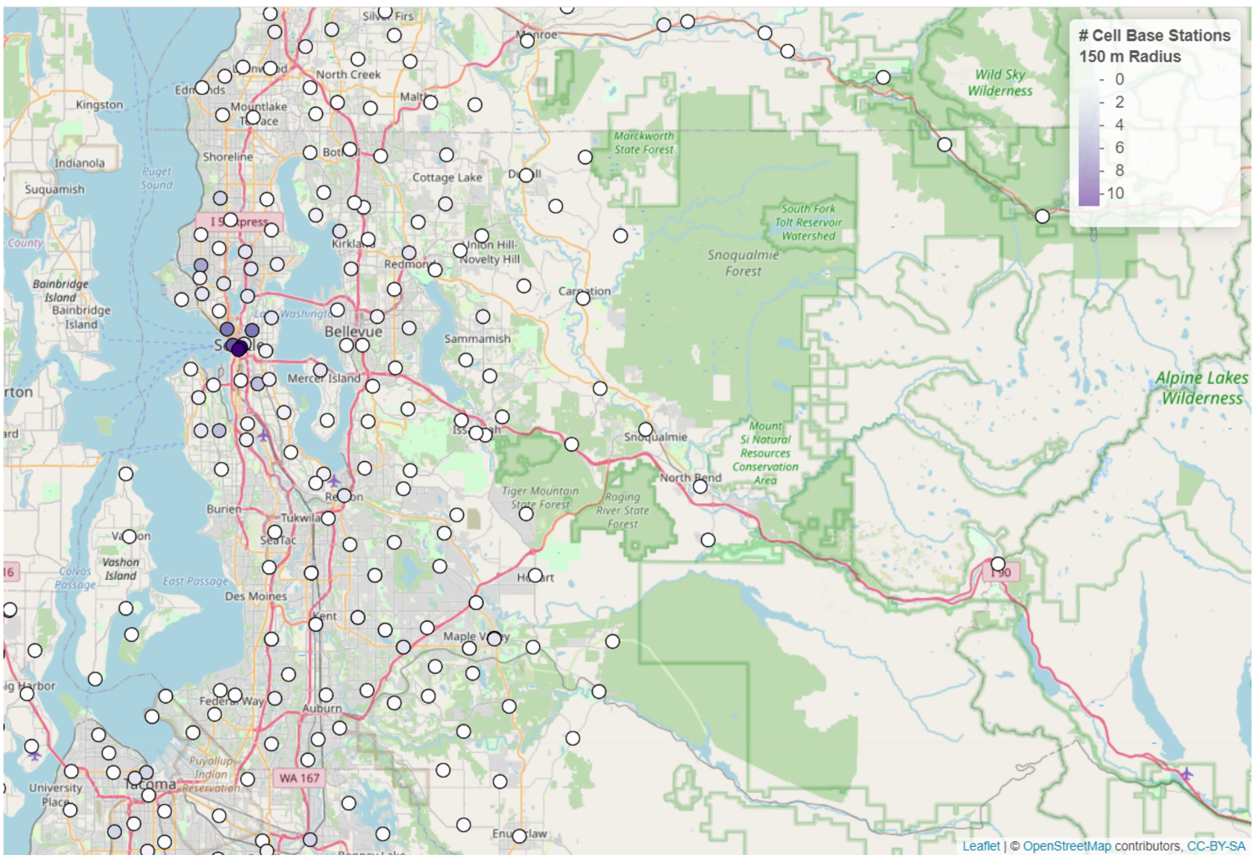

Figure 3. Final plot showing fire stations with their number of proximal cell towers

With this information we selected 13 fire stations from which to collect outdoor RF exposure data. There were no fire stations classified as rural within our participating fire districts, so we ultimately selected 7 suburban fire stations, and 6 urban fire stations. These fire stations had a range of 0 to 7 proximal cell towers identified by our selection process.

Fire Service	Fire Station Number	Urbanicity Coding	# of proximal cell towers
A	A1	Suburban	2
A	A2	Suburban	1
A	A3	Suburban	2
A	A4	Urban	0
A	A5	Suburban	0
B	B1	Urban	2
B	B2	Urban	7
B	B3	Suburban	0
C	C1	Suburban	0
C	C2	Suburban	0
C	C3	Urban	2
C	C4	Urban	0
C	C5	Urban	0

Table 1. Outdoor fire station sampling distribution.

*Fire districts and fire stations have been kept anonymous for privacy reasons

Outdoor Fire Station Sampling

After fire stations were selected, site visits were scheduled with our contacts within each fire district. To collect RF exposure data during these site visits, a broad-band spectrum analyzer (Aaronia Spectran HF 60xx V4) was used. This device was operated while connected via USB to a laptop that was running the MCS Spectrum Analyzer software. The omnidirectional antenna (omnilog) was worn by the researcher at chest height while the software logged exposure from 1MHz through 9 GHz at 0.5 MHz intervals. We later determined that the omnilog antenna was calibrated to collect data from 300MHZ to 8GHz. The hyperlog antenna was calibrated to collect data from 680 MHz through 9 GHz. In our data cleaning process the values outside of this range were removed from the data.This process compensated for the antennae gain of 2 dBi for the Omnilog and 5 dBi for the Hyperlog. While logging exposure as well as the GPS coordinates, where possible, a researcher walked around the perimeter of the fire. Perimeter walks were limited according to the landscape and things such as fences and private property boundaries. The researcher stood still for 2-minute intervals to allow for a full sweep of the frequencies being measured. This was done twice, once near the fire station, and once from a wider radius from the fire station. After these two samples were recorded with the omnidirectional antenna (omnilog), the antenna was switched to a directional antenna (Hyperlog), and a short duration sample was taken. This directional sample was taken by standing in the fire station parking lot with the antenna held horizontally at chest height while aimed at the fire station. After 2 minutes, the researcher turned 90 degrees with the Hyperlog antenna and sampled for another 2 minutes. This process was repeated until the researcher concluded at the original orientation with a total directional sample time of 8-minutes.

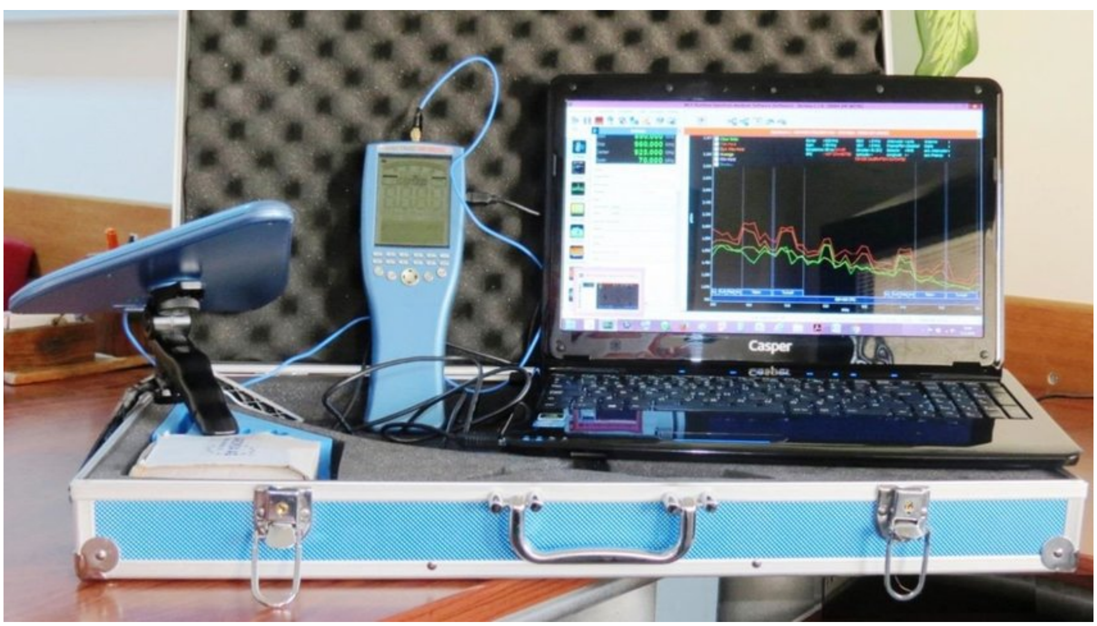

Figure 4. Sampling setup with hyperlog antenna attached

*Our setup was done with the laptop running within a backpack

Indoor Fire Station Sampling

10 of the stations sampled for outdoor RF exposure were later sampled for indoor RF exposure. Site visits were scheduled with fire service contacts. The researcher walked through each fire station while operating the Aaronia Spectran HF with the Omnilog antenna attached. During the walkthroughs, the researcher visualized the most recent sweep (scan from 300MHz to 8GHz) of RF exposure as well as the maximum intensity of RF exposure simultaneously. This allowed the researcher to compare RF exposure in different areas of the fire station. Once an area of detectable RF exposure was found, the sampling equipment was placed in the area and plugged into a power source and left there to collect RF exposure measurements for between 24 and 72 hours.

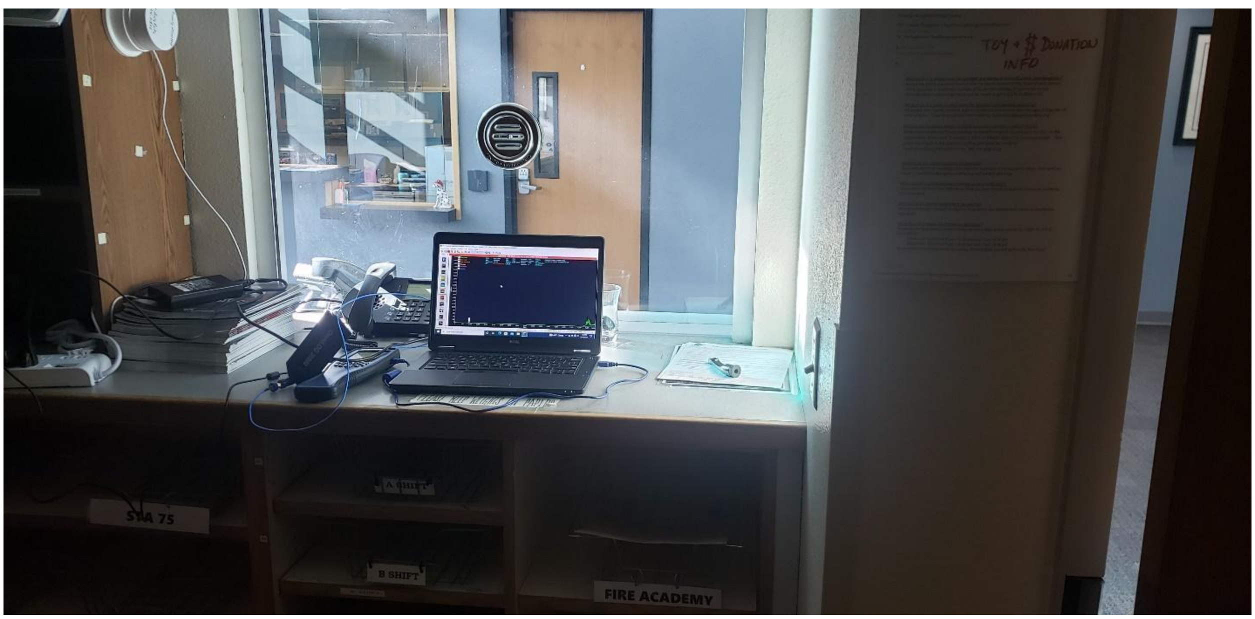

Figure 5. Indoor overnight sampling done in fire station lobby

Figure 6. Indoor overnight sampling done inside fire station garage

Pittsburgh Sleep Quality Index

The Pittsburgh Sleep Quality Index (PSQI) is a validated sleep questionnaire that surveys individuals on 7 sleep quality components and scores each component from 0-3. These components are sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleeping medication, and daytime dysfunction. Each component is scored from 0-3, with 0 indicating the least amount of detriment to sleep, and 3 indicating the highest amount of detriment to sleep. Summing the scores from all 7 components provides a global PSQI score with lower scores indicating better sleepers and higher scores indicating poorer sleepers. A global PSQI score>5 is indicative of a poor sleeper with a diagnostic sensitivity of 89.6% and specificity of 86.5% (Buysse et al., 1989).

Firefighters generally work long shifts, typically 24 hours on shift followed by 48 hours off shift, or 10 to 12 hour shifts three or four days in a row (Bureau of Labor and Statistics, 2022).While on shift, firefighters often do not get healthy amounts of sleep due to work demands, *e.g.*, responding to calls during normal sleep hours. One of the goals of this study was to compare a fire station's RF exposure to PSQI score, but sleep disruption from work disturbances proved to be a confounding variable. In an effort to control for this, we modified the PSQI survey to ask questions specifically about when firefighters were not on shift. We also added three questions that were specific to our study:

1. Which fire district do you work for?
2. Which fire station has been your primary station during the last 30 days?
3. About how many nights in the last 30 days were you on shift?

These questions were asked so that we could attempt to stratify our analysis by fire district and station RF exposure. With these modifications, we sent out our version of the PSQI to our contacts at the participating fire services who had worked with us to schedule site visits for RF sampling.

RF Sampling Data Analysis

To understand our RF site exposure data, we loaded the samples into the Department of Occupational and Environmental Health remote server, operating the statistical software R (R version 4.1.3 (One Push-Up). These files were imported with a custom-built function called "import_xml" that is included in the appendix. This function loaded in the data, applied antennae specific calibrations to the raw data, converted the RF intensity from dBm to volts per meter (V/m) using conversion tables provided by the instrument manual (Aaronia Instrument Manual, 2013), and compared the V/m at each frequency to both the ICNIRP population and the ICNIRP occupational guidelines. Electrical field measurements were converted to Power Density using conversion tables provided by the manufacturer (Aaronia Manual, section 12). These conversions are dependent on the central frequency of the assumed source. We assumed a central frequency of 1550 MHz) which was the recommendation for unknown signal sources and represents a weighted average of frequencies between 900 MHz and 2.4 GHz and is expected to provide an accuracy of approximately +/- 4 dB. One of the primary benefits of examining our measured RF exposure in terms of the ICNIRP guideline is that it accounts for varying specific absorption rates. Specific absorption rate is a measure of the rate at which energy is absorbed per unit mass by a human body when exposed to a RF field. This means that the body more readily absorbs RF energy at certain frequencies. The ICNIRP exposure guidelines are not uniform across the electromagnetic spectrum and vary depending on the frequency in order to count for varying absorbance rates.

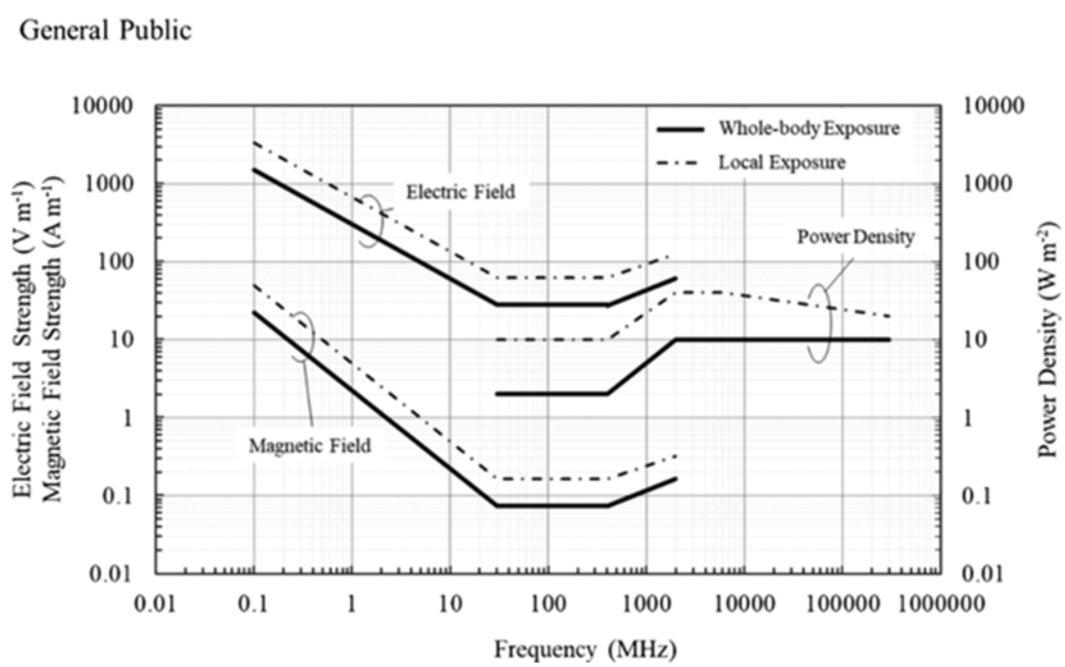

Figure 7. General public ICNIRP guidelines (ICNIRP, 2020.)

While analyzing the data from our outdoor fire station sampling, we became concerned about two potential issues with our data. The first concern was that of potential instrument noise. This is the phenomenon of RF intensity being recorded as artificially high in the higher frequencies as an artifact of sampling through such a wide range of frequencies. The other potential issue of concern was that the RF sampling device could itself be generating some amount of RF. To compensate for these potential issues, background samples were collected with the antennae enclosed within a Faraday cage, which is an enclosure designed to block electromagnetic fields. When viewing the samples taken with antennae enclosed in a Faraday cage (theoretically RF free environment), we discovered that some amount of RF was still being detected.

Figure 8. Faraday cage used in this study

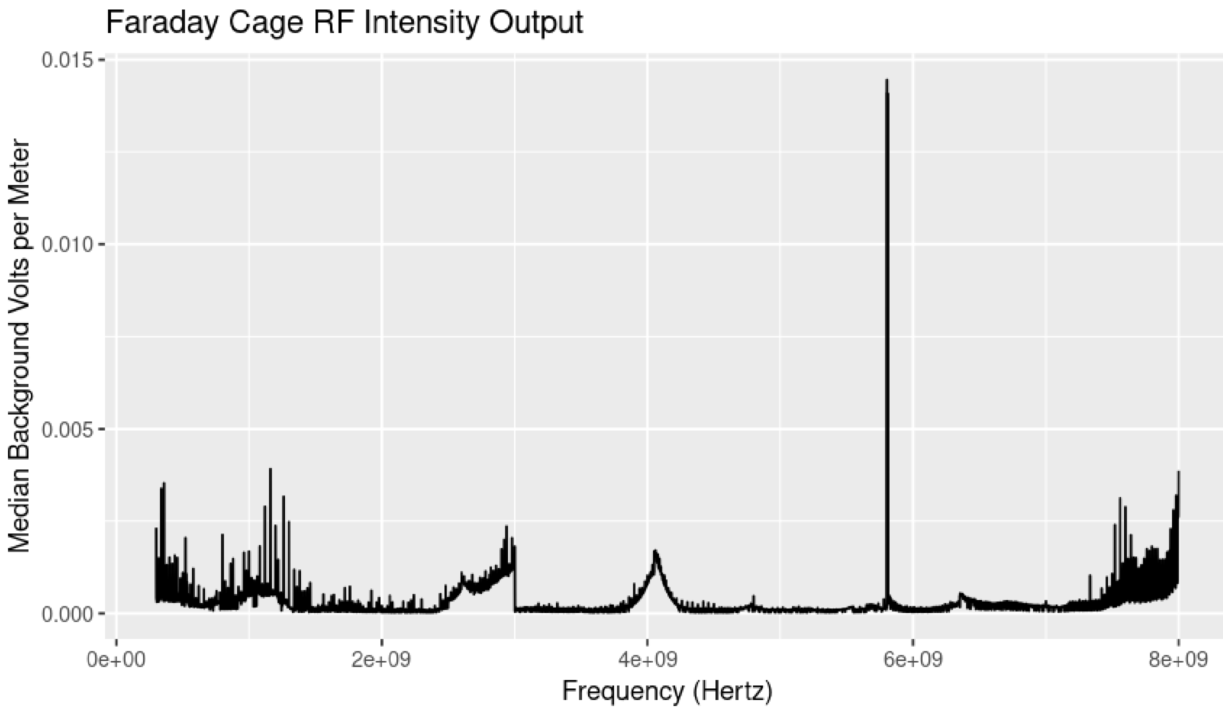

Figure 9. Omnilog RF intensity within a Faraday cage

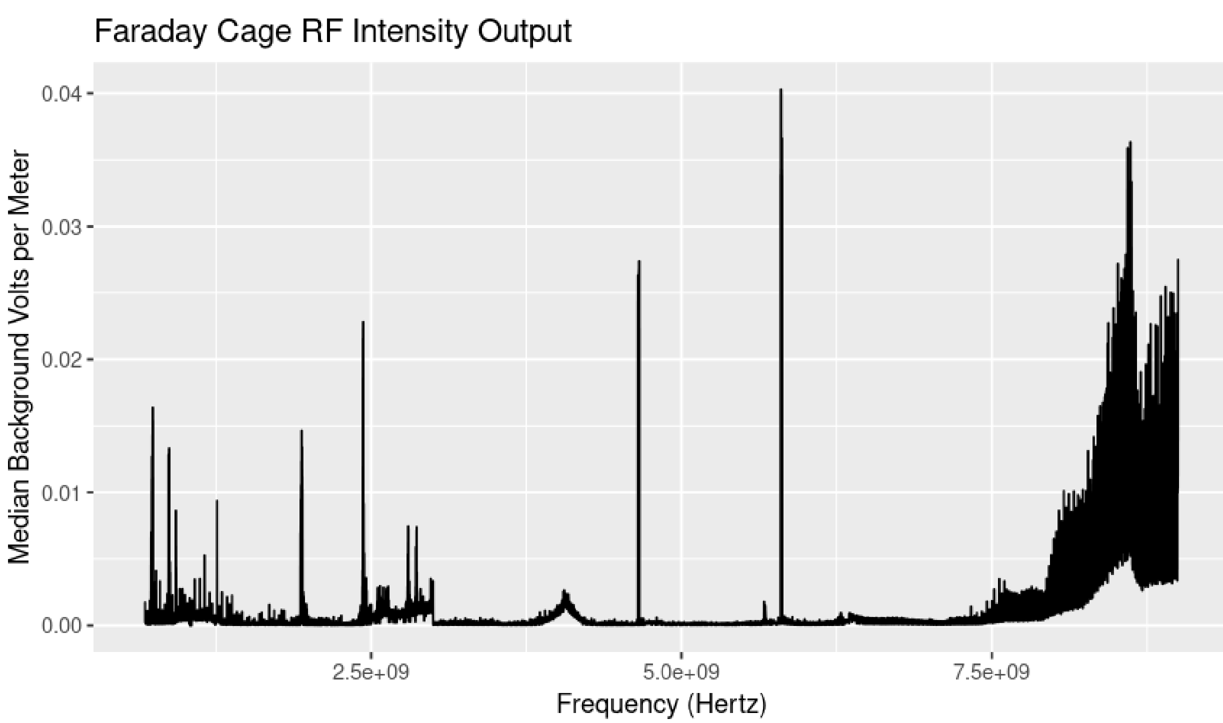

Figure 10. Hyperlog RF intensity within a Faraday cage

To compensate for this background RF that our monitor was detecting, we took the Faraday cage sample V/m values and calculated the standard deviation of RF intensity at each frequency. The standard deviation was multiplied by 3 and then multiplied by the median Faraday intensity for each frequency. This was done because in a normal distribution of data, 99.7% of data should be within 3 standard deviations of the mean. In this case, we used the median to be less influenced by outliers. This gave us an intensity at every 0.5MHz from 300 MHz to 8GHZ that could be background RF from the device itself. These background intensities from 300MHz to 8GHZ were deemed “Faraday Limit of Detection”.We then only kept the measurements above the Faraday limit of detection in our collected samples. This was done for both the omnilog and hyperlog antennas. This was done with another custom "R” function we created for this project called “process_rdata” (Grolemund & Wickham, 2011; Wickham, 2011, 2011, 2016; Wickham et al., 2022). This function took the median RF intensities for each sample from their multiple sweeps through the range of frequencies sampled. It then took a 95th-quantile value for the RF intensities measured to capture important sources of RF exposure data. RF is distributed in an inverse square manner, meaning that if we were twice the distance from the RF source, we would be collecting one fourth of the exposure. Considering that firefighters move in space around the station, used the 95th quantile of data to represent the possible increase in exposure firefighters could have based on the inverse square law that governs RF distribution.

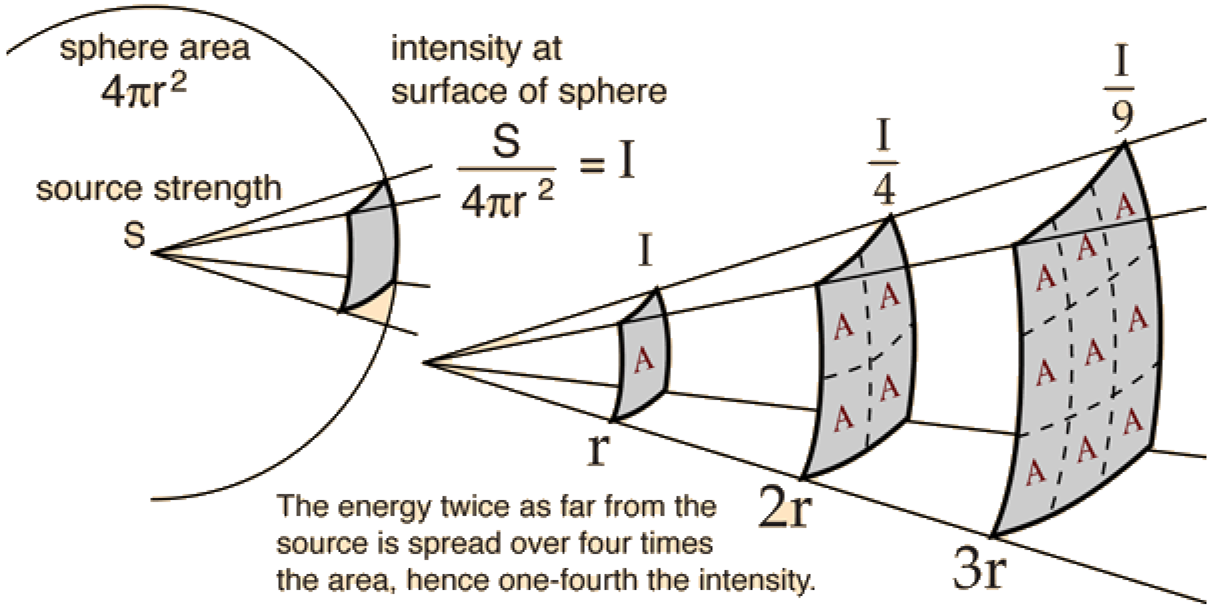

Figure 11. Inverse Square Law visualized

We took the background and multiplied by 3 times the standard deviation from the median sweep. The sampled frequencies were subset to match the manufacturer's suggested range for the used antennae. This range was 300 MHz to 8 GHz for the omnilog antenna, and 680 MHZ to 9 GHZ for the hyperlog antenna. Output was saved as an Excel file that included the 20 frequencies with the highest RF exposure and their associated intensities. The frequencies above the background levels for the 95th quantile V/m measurements for the median sweep were plotted.The median V/m by frequency for the median sweep of the sample was plotted. Finally, the function created an Excel file with the sum of the percentage of the ICNIRP guidelines (population and occupational) across the frequencies. The percentage of the ICNIRP guidelines was calculated at each frequency by comparing the measured V/m to the guideline V/m. These effects are additive across the electromagnetic spectrum, thus the percentage of the ICNIRP guideline is summed for all frequencies monitored. The code for this function is included in the appendix.

PSQI Survey Response Analysis

The survey was sent out via email to the health and safety partners within the participating fire services who then emailed the survey to firefighters. Before being able to access the PSQI, respondents were required to review and sign an IRB approved consent form. Surveys that were incomplete and thus could not be accurately scored were removed from the analysis. In addition, errors in input time (military vs AM/PM time indicators were corrected when bedtime was inconsistent with wakeup time. After removing incomplete responses and correcting for military time, the remaining survey responses were imported to 'R," where each survey response had its 7 components scored and a global score (sum of the seven components) was calculated based on the validated scoring guide (Buysse et al., 1989). I also created a series of new variables, including one indicating if a participant received 6 hours of sleep or less. This cutoff has previously been used to define short sleep duration (Luckhaupt et al., 2010b). We also computed a variable to indicate if a PSQI global score (sum of 7 component scores) was less than or equal to 5. This cutoff is used by the developers of the PSQI to distinguish good and poor sleepers (Buysse et al., 1989). A global PSQI score below or equal to 5 indicates a good sleeper, while a global PSQI score above 5 indicates a poor sleeper. With these created variables, it was possible to do a series of regressions using various predictors and PSQI score as the outcome. One regression model created using the "lm" function within R used number nights on shift in the last 30 days binned to the nearest multiple of three and short sleep as the independent variables, and global PSQI score as the dependent variable. An interactive and an additive regression were created and subsequently compared to see which better explained the relationship between the variables. 7 regressions were created with number of nights on shift in the last 30 days as the independent variable, and each respective PSQI component score as the dependent variable. Finally the PSQI responses from firefighters who primarily worked in a fire station that was sampled for area RF exposure were merged with a dataset containing the RF measurements for the station, outdoor hyperlog, outdoor omnilog, and indoor omnilog. These three measures were represented in terms of their percent of the ICNIRP occupational guideline. 3 regressions were created using each measure of RF exposure as the independent variable and global PSQI score as the dependent variable.

Results

RF Sampling Results

After processing our outdoor RF data, we were able to summarize the percent of the ICNIRP occupational exposure guideline each station had for our outdoor omnilog samples, outdoor hyperlog samples, and indoor omnilog samples. The outdoor omnilog samples ranged from 0.056% to 0.375% of the ICNIRP occupational guideline. The outdoor hyperlog samples ranged from 0.052% to 0.308% of the ICNIRP occupational guideline. The indoor omnilog samples ranged in exposure from 0.098%-0.346% of the ICNIRP occupational guideline. Significantly, all of these measurements are well below the ICNIRP occupational guideline. However, this guideline is gauged to prevent levels of RF exposure that are high enough to raise body tissue temperature. The guidelines do not contemplate whether there are any effects of exposure outside of tissue damage from excess heating.

Several fire stations had noticeable differences in RF exposure inside compared to outside. This is shown in table 3, where stations A4(0.256% indoor vs 0.106 outdoor), A5(0.269 indoor vs 0.105 outdoor), and C4 (0.319% indoor vs 0.130% outdoor) had much larger RF exposures in terms of the percentage of the ICNIRP guidelines for indoor measurements than for outdoor measurements. This is consistent with the amount of shielding that the concrete structure of a firehouse would provide for RF exposure. This is discussed further in the discussion section, but it also provides evidence that RF is being generated within the fire station and supports the idea that our instrument was able to detect low level variation in RF exposure. In figure 17. We plotted our stations with color indicating the presence of cell towers or not. The y-axis is the directional antenna output in terms of the ICNIRP guideline which is better suited to detect cell tower RF than the omnidirectional antenna. This plot shows low correlation between known cell proximal cell towers and measured RF exposure.

Fire Service	Fire Station Number	Urbanicity Coding	# of proximal cell towers	Outdoor omnilog % of ICNIRP	Outdoor hyperlog % of ICNIRP	Indoor omnilog % of ICNIRP
A	A1	Suburban	2	0.2	0.1	0.1
A	A2	Suburban	1	0.1	0.1	0.1
A	A3	Suburban	2	0.1	0.1	0.1
A	A4	Urban	0	0.1	0.1	0.3
A	A5	Suburban	0	0.1	0.1	0.3
B	B1	Urban	2	0.1	0.1	data not collected
B	B2	Urban	7	0.4	0.1	data not collected
B	B3	Suburban	0	0.1	0.1	data not collected
C	C1	Suburban	0	0.3	0.3	0.3
C	C2	Suburban	0	0.2	0.1	0.1
C	C3	Urban	2	0.2	data not collected	0.1
C	C4	Urban	0	0.1	0.1	0.3
C	C5	Urban	0	0.2	0.3	0.1

Table 2. RF exposure measures by fire station

Fire Station Number	Outdoor omnilog % of ICNIRP	Indoor omnilog % of ICNIRP	ratio of indoor vs outdoor	Known Proximal Cell Tower?
A1	0.2	0.1	0.7	Yes
A2	0.1	0.1	1.8	Yes
A3	0.1	0.1	0.9	Yes
A4	0.1	0.3	2.4	No
A5	0.1	0.3	2.6	No
B1	0.1	data not collected	N/A	Yes
B2	0.4	data not collected	N/A	Yes
B3	0.1	data not collected	N/A	No
C1	0.3	0.3	1.4	No
C2	0.2	0.1	0.8	No
C3	0.2	0.1	0.9	Yes
C4	0.1	0.3	2.4	Yes
C5	0.2	0.1	0.7	Yes

Table 3. Ratio of Indoor vs Outdoor RF exposure by Station

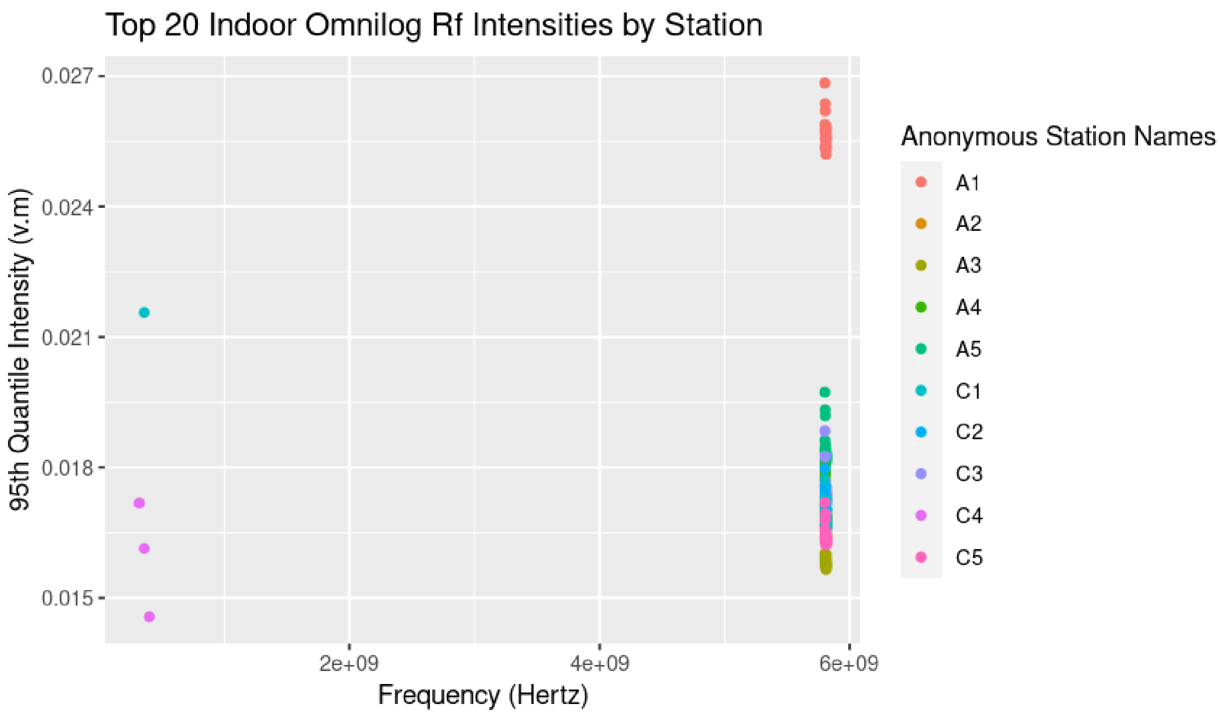

Figure 12. Indoor Omnilog top 20 frequencies with highest intensity by stations.

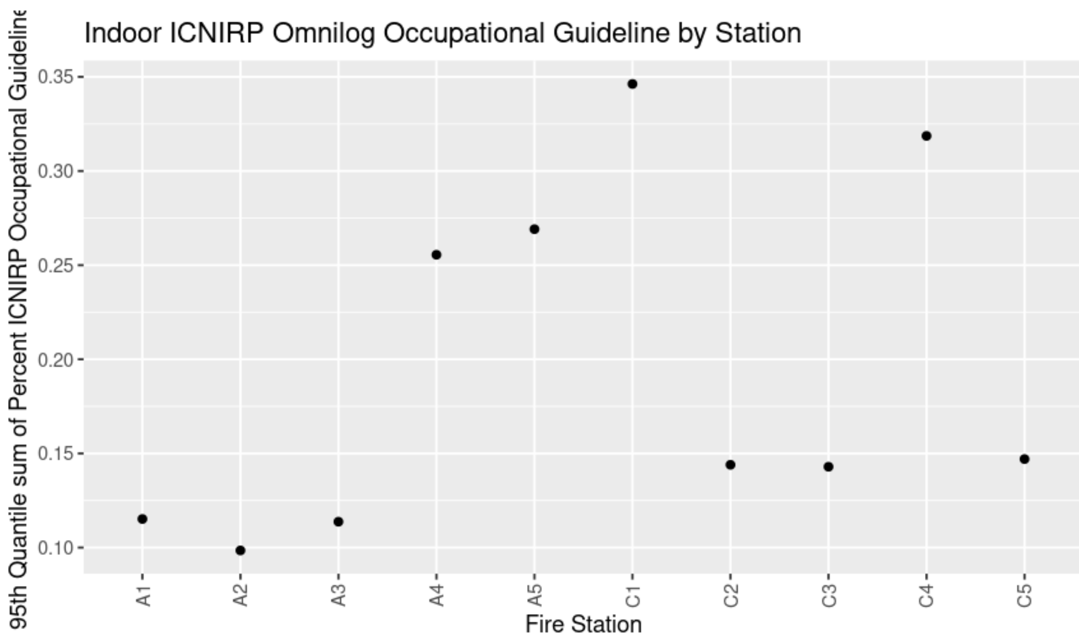

Figure 13. Indoor omnilog percent of ICNIRP occupational guideline by station

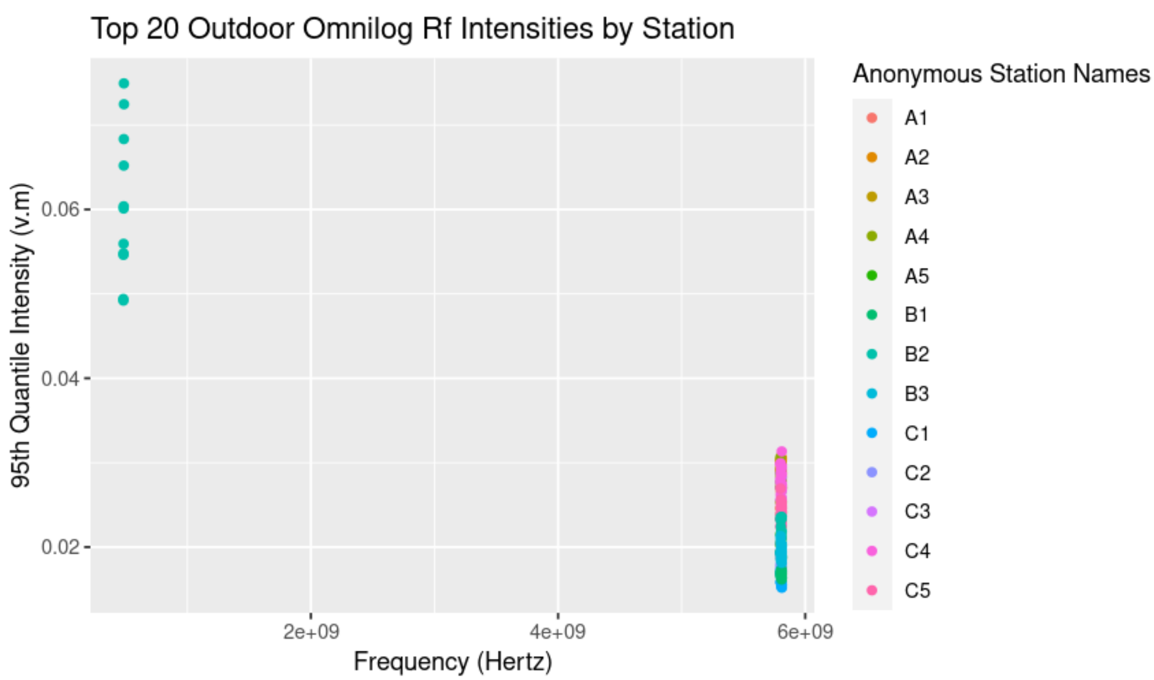

Figure 14. Outdoor omnilog top 20 frequencies with highest intensities by station

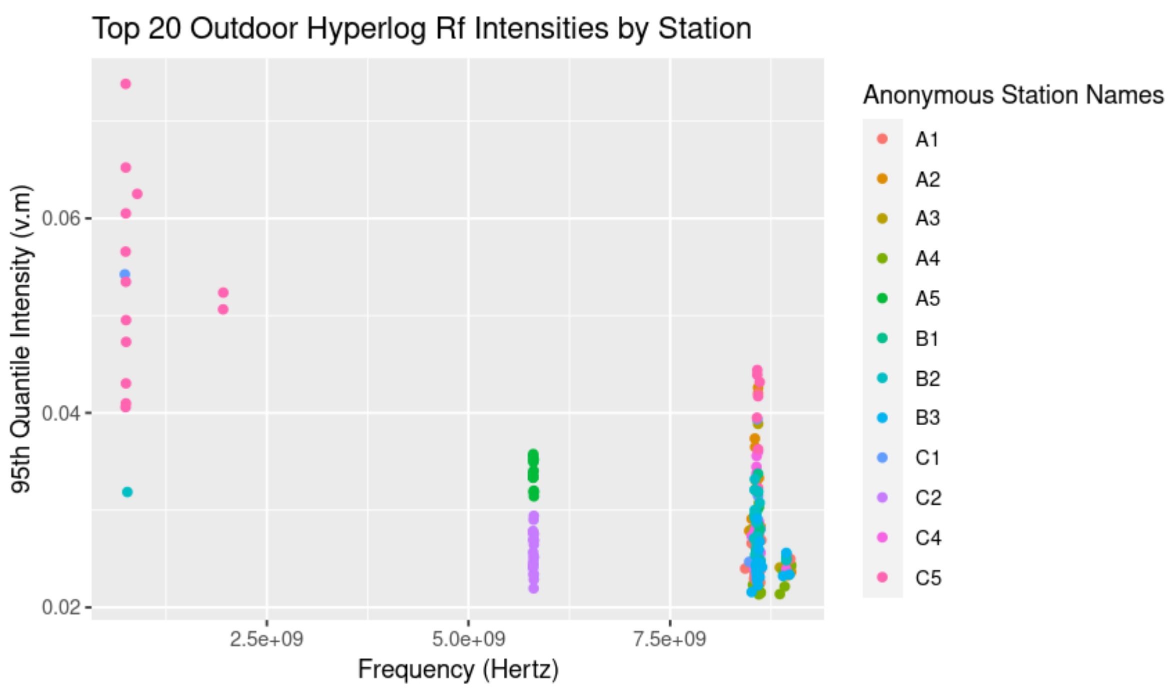

Figure 15. Outdoor hyperlog 20 frequencies with highest RF intensities by station

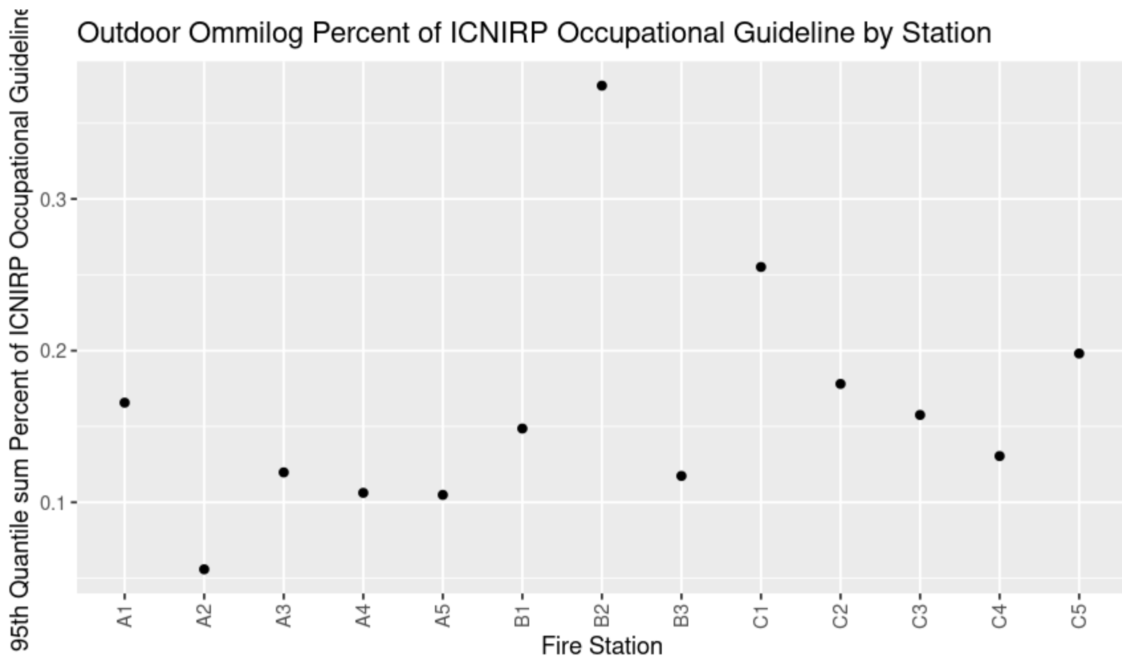

Figure 16. Outdoor omnilog percent of ICNIRP occupational guideline by station

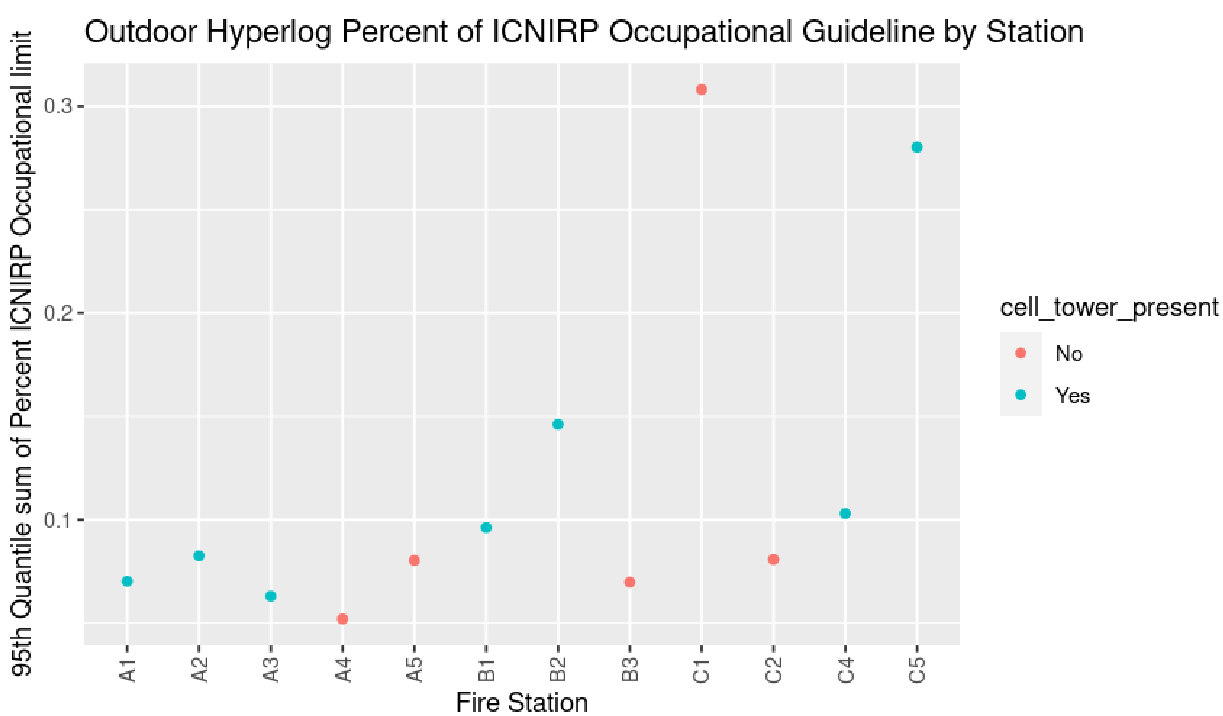

Figure 17. Outdoor hyperlog percent of ICNIRP occupational guideline by station

PSQI Survey Results

Of the 151 surveys collected, seven incomplete surveys were removed from the analysis. We are assuming that one of our initially participating fire districts was unable to send out the survey to its firefighters which resulted in zero responses from that district. Of the districts with survey responses, there are a total of 844 employed firefighters. This gives us a survey response rate of roughly 18% (151/844). This is somewhat less than the response rate of other studies involving the PSQI. A study of the impact of shift work among nurses published in 2017 had a response rate of 34% (McDowall et al., 2017). Another 2017 study evaluating the impact of working hours on sleep had a response rate of 23%. (Afonso et al., 2017). 36 of our 144 completed surveys had their bedtime modified to fit the military time format. The complete survey responses were processed through "R". We found that 42 (29%) of our complete survey responders were classified as good sleepers. Conversely, 102 (71%) of our respondents were classified as poor sleepers (global PSQI score > 5). In addition, another metric used to evaluate sleep, short sleep duration revealed that 53 (37%) of our respondents reported that on average while not on shift, they have short sleep duration as defined by getting 6 hours of sleep or less. Our median global PSQI score for the 144 completed surveys was 7.5.

Fire District	n	mean	SD	Median	Min	Max	SE
A	52	7.9	3.1	8.0	2.0	17.0	0.4
C	3	6.7	0.6	7.0	6.0	7.0	0.3
D	89	7.9	3.8	7.0	1.0	17.0	0.4

Table 4. PSQI score summaries by fire district

Component	Fire District	n	mean	SD	Median	Min	Max	SE
1	A	52	1.3	0.9	1	0	3	0.1
1	C	3	1.3	0.6	1	1	2	0.3
1	D	89	1.4	0.8	1	0	3	0.1
2	A	52	1.3	1.0	1	0	3	0.1
2	C	3	1.7	1.2	1	1	3	0.7
2	D	89	1.3	1.0	1	0	3	0.1
3	A	52	0.6	0.8	0	0	3	0.1
3	C	3	0.0	0.0	0	0	0	0.0
3	D	89	0.6	0.9	0	0	3	0.1
4	A	52	1.0	1.1	1	0	3	0.2
4	C	3	0.0	0.0	0	0	0	0.0
4	D	89	1.1	1.2	1	0	3	0.1
5	A	52	1.5	0.6	1	1	3	0.1
5	C	3	1.7	0.6	2	1	2	0.3
5	D	89	1.5	0.5	1	1	2	0.1
6	A	52	1.3	0.6	1	0	2	0.1
6	C	3	1.3	0.6	1	1	2	0.3
6	D	89	1.2	0.6	1	0	3	0.1
7	A	52	0.9	0.9	1	0	3	0.1
7	C	3	0.7	0.6	1	0	1	0.3
7	D	89	0.9	0.9	1	0	3	0.1

Table 5. PSQI component summary by fire district

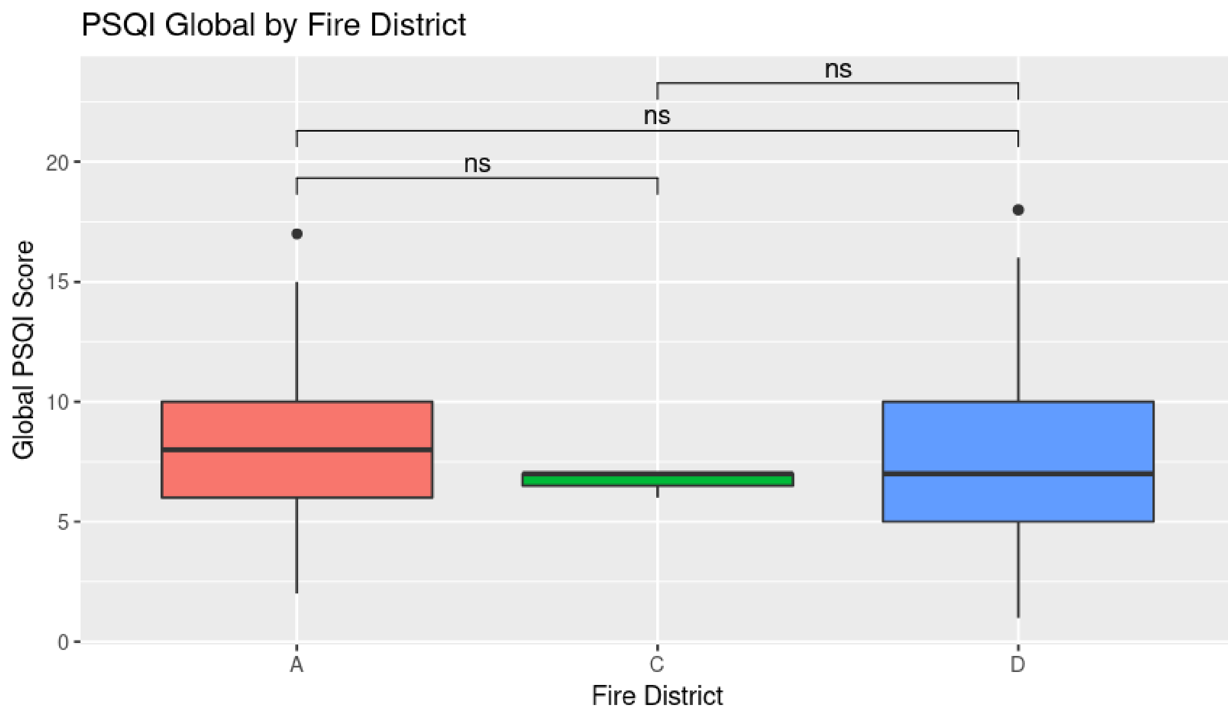

Figure 18. PSQI global score boxplots by fire district

PSQI Regressions

We were able to run a regression with "number of nights on shift in the last 30 days rounded to the nearest multiple of 3" and "6 hours of sleep or less" as the independent variables. We used PSQI score as the dependent variable. We used bins that rounded the number of nights on shift to the nearest multiple of 3 to smooth out or better analogize the relationship. The output of this regression in full is included in the appendix. The best fit model for this data is as follows:

$$PSQI\ score = 4.91 + 0.14X_1 + 3.45I(X_2) + 0.15X_1 * I(X_2) + \varepsilon_i$$

*Where X1 = nights on shift in last month binned to nearest multiple of 3

$I(X_2)$ = 0 if the respondent has greater than 6 hours of sleep,

1 if the respondent has 6 hours of sleep or less

ε_i = where the errors are assumed to be normally distributed, centered around zero, with a single standard deviation

This relationship is shown in the plot below.

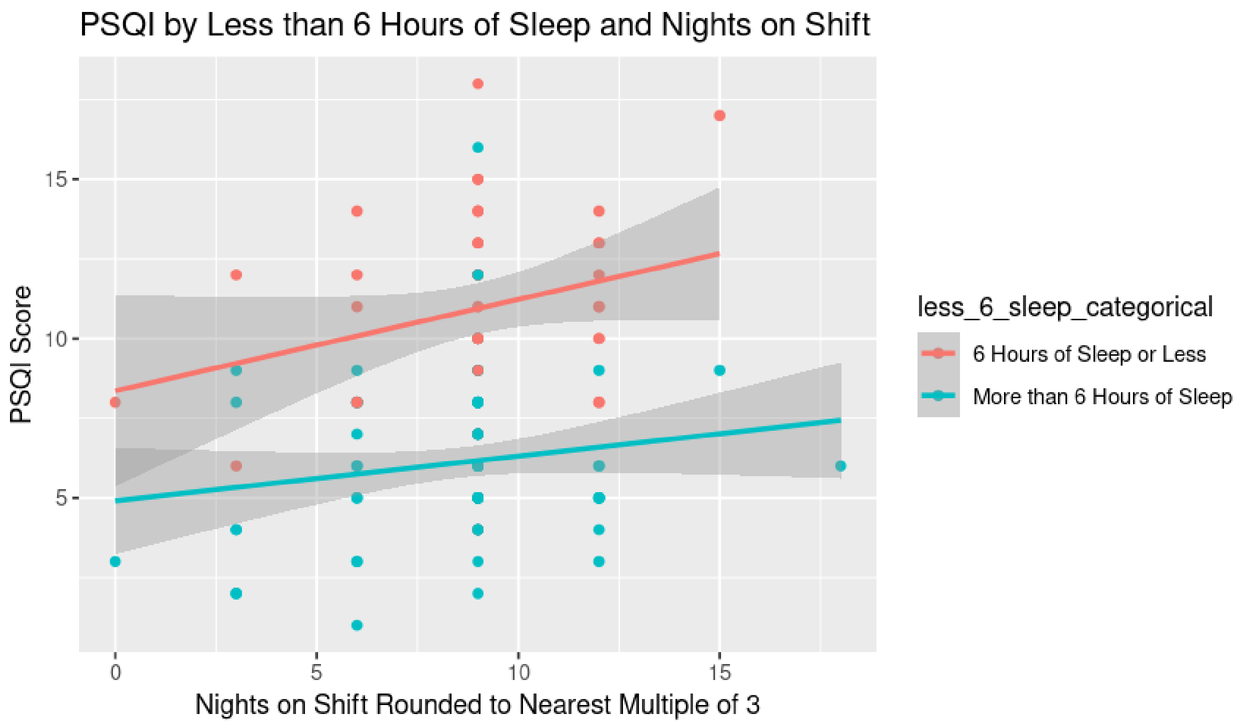

Figure 19. PSQI scores by nights on shift binned to nearest multiple of 3

We found a suggestion that the total nights on shift increases the risk of sleep disturbance in this population (p = 0.18), after accounting for differences observed in those with underlying short sleep as compared to the rest of the sample. We did not find evidence that there was a strong interaction between nights on shift and short-sleep on PSQI score (p = 0.4). This model has an adjusted r squared value of 0.47, indicating that 47% of the variability in PSQI global score is explained by this model. This data has a somewhat linear relationship, is normally distributed, has equal variance, and does not have influential points. The diagnostic plots confirming this can be found in the appendix.

We then created a regression model without the predictors interacting, making it an additive model. This additive regression model stated that:

$$PSQI\ score\ =\ 4.5\ +\ 0.2\ +\ 4.8(X_2)\ +\ \varepsilon_i$$

*Where X1= nights on shift in last month binned to nearest multiple of 3

$I(X_2)$= 0 if the respondent has greater than 6 hours of sleep,

1 if the respondent has 6 hours of sleep or less

ε_i= where the errors are assumed to be normally distributed, centered around zero, with a single standard deviation

We found an association between total nights on shift and our results indicated that for an increase in 3 total nights on shift, there was a 0.2 (p=0.02) increase in PSQI score after controlling for differences in baseline PSQI score for those with short sleep.

This data has a somewhat linear relationship, is normally distributed, has equal variance, and does not have influential points. The diagnostic plots confirming this can be found in the appendix.

To determine which of these models is a better fit for our data, we used Akaike Information Criterion (AIC) (Portet, 2020). Our multiplicative model had an AIC value of 674.6, and our additive model had an AIC value of 673.3. This led us to determine that the additive model is a better fit for our data.

We created regressions using nights on shift in the last month binned to the nearest multiple of 3 as a predictor of each PSQI component score. The linear model stated that

$$Component\ 1\ score\ =\ 0.9\ +\ 0.1\left(X_1\right) + \varepsilon_i$$

*where, X_1= Nights on shift in the last month binned to the nearest multiple of 3

ε_i= where the errors are assumed to be normally distributed, centered around zero, with a single standard deviation

We found a statistically suggestive relationship between total nights on shift and our results indicated that for an increase of 3 total nights on shift, there was a 0.1 (p=0.06) increase in global PSQI score when not controlling for differences in baseline PSQI score for those with short sleep. This model had an adjusted r squared of 0.017, meaning that variation in nights on shift in the last month binned to the nearest multiple of 3 explains less than 2% of the variation in Component 1 PSQI scores. The regressions and plots for the other 6 components were, in general, less statistically significant and had similar adjusted r squared values. These plots and regressions are included in the appendix.

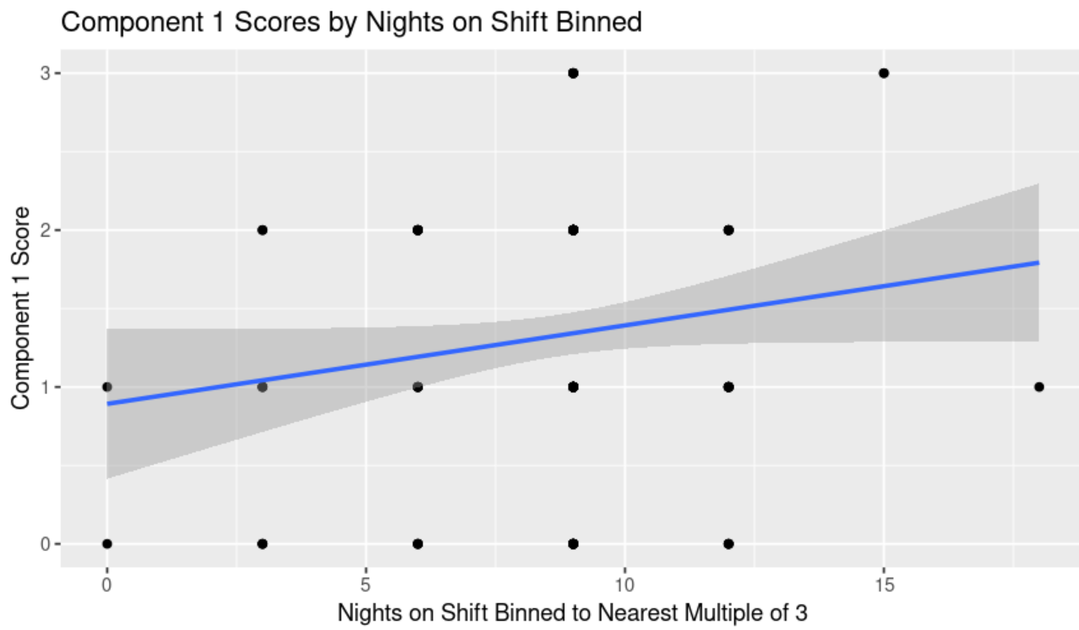

Figure 20. Subjective sleep quality PSQI scores by binned nights on shift

Of the 144 complete PSQI survey responses, 21 were from participants whose primary station during the previous month coincided with fire stations sampled for RF exposure. These 21 survey responses were from a total of 6 fire stations. This small sample size means that any regressions performed using RF measurements as a predictor and PSQI scores as the outcome lack significant power. However, these regressions were still conducted to show what researchers could look for when doing a similar study with a higher number of PSQI respondents from stations sampled for RF. It would be even better to get PSQI responses from firefighters who had their personal RF levels monitored.

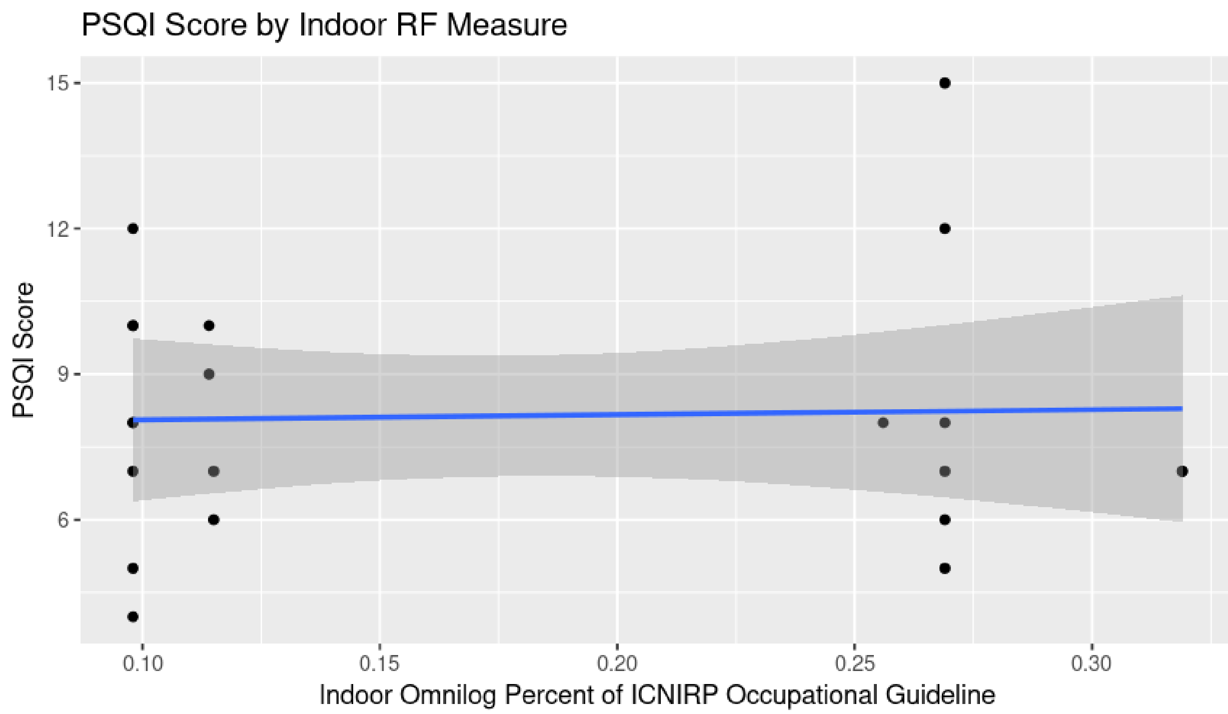

Figure 21. PSQI score by indoor omnilog percent of ICNIRP occupation guideline

This regression provided the following equation

$$PSQI\ score\ =\ 8.0\ +\ 1.0(X_1) +\ \varepsilon_i$$

*where X_1=Percent of ICNIRP Occupational Guideline measured

ε_i= where the errors are assumed to be normally distributed, centered around zero, with a single standard deviation

We did not find a statistically relevant relationship between percent of the ICNIRP occupational guideline measured at a fire station and respondents PSQI scores (p=0.88). This is to be expected with the limited number of sampled fire stations that had corresponding survey responses.

Discussion

It is apparent that the OpenCellId database is incomplete because two fire stations categorized as having 0 proximal cell towers were noted to have proximal cell towers when sampled for outdoor RF exposure.

Figure 22. Cell Tower on site of sampled fire station not detected by OpenCellID

23. Cell tower on site of sampled fire station not detected by OpenCellID

Figure 24. Warning label on base of above shown cell tower

We also used area measurements of RF exposure at fire stations as estimates of personal RF exposure when using area RF measurements as a predictor of PSQI scores. However, a better metric would have been personal exposure measurements if we had collected them. We had initially aimed to collect personal RF exposure measurements as well as real sleep data and heart rate variability data, but the COVID-19 pandemic interfered with our ability to collect personal exposure and health outcome data from participants. In our future studies section, we discuss the way this information could be collected going forward. In the PSQI analysis we used getting 6 hours of sleep or less (on average) a night as a predictor of PSQI scores. This has some level of redundancy because hours of sleep per night is directly analyzed for the sleep duration component of the scoring guide. One of the limitations of our RF measurement device is that it only samples for high frequency radio frequency radiation, and not low frequency electro-magnetic frequency radiation. Low frequency electro-magnetic frequency radiation exists at 60 hertz frequency and is associated with power transmission lines and household wiring and appliances. Unfortunately, our instrument is incapable of sampling for frequencies this low. As such, our measurements do not include EMF radiation.

We were unable to get PSQI survey responses from firefighters primarily working in all of the fire stations we sampled for RF exposure. In communication with our firefighter partners, the survey was sent out to firefighters who worked in the sampled fire stations. One of the fire districts had recently had a number of optional online surveys distributed to its members and our contact from the district suspected that there was survey fatigue that impacted willingness to participate with our survey. Ways to confront this survey fatigue moving forward would be to include participation incentives, and visit the fire stations and ask for participants in person. Including our question of “how many nights have you been on shift in the last 30 days” in the survey allowed us to determine that an increase in nights on shift increases the risk of sleep disturbance ($p=0.02$) after controlling for getting short sleep. This indicates that if firefighters wish to combat sleep disruption, an intervention could be targeted at individuals with a high number of nights on shift.

Future Studies

In future RF exposure studies, the collection of personal RF exposure would be a better metric of RF exposure, instead of or in addition to area RF exposure measurements. As a part of this study, we identified the “EME SPY Evolution" as a potential instrument capable of collecting personal RF exposure data. This instrument collects data in up to 20 predefined bands. The manufacturer has both U.S., E.U., and Asia specific RF bands. The instrument software produces data in the form of volts per meter, microwatts per centimeter squared, watts per meter squared, percent of general exposure ICNIRP guideline, and percent of occupational exposure ICNIRP guideline for each RF band at each instantaneous measurement. The researcher for this study successfully monitored RF exposure among industrial microwave operators at a seafood processing facility using this instrument. One notable limitation for this instrument is that it does not monitor continuously throughout the RF frequency range and therefore has “blind spots' ' between the bands that it measures where it is unable to collect RF data. Additionally, this instrument is only capable of monitoring RF exposure from bands that range from 87 MHz-107 MHz to 5.15 GHz-5.85 GHZ. This means that in addition to blind spots between sampling bands, the instrument also fails to capture exposure below 87 MHz and above 5.85 GHz.

Similar to our RF measurements, our sleep data was also not a direct measurement. To improve upon study design in the future, actual sleep data could be collected instead of or in addition to proxy data in the form of PSQI survey responses. We identified the ActiGraph GT9X Link as a good potential instrument for collecting sleep data and activity.

Finally, a future study could further explore the relationship between RF exposure and hypertension (Y. Wang et al., 2015), as well as any correlation with cardiovascular disease. Studies have found that lower heart rate variability (HRV) is associated with a higher risk of all causes of death and cardiovascular events (Fang et al., 2020). Even though it is not a direct measure of hypertension and cardiovascular disease, HRV would be a good indicator measure (Thayer et al., 2010). We identified the Firstbeat Bodyguard 3 as a good potential HRV monitoring device. This device collects HRV through two ECG electrodes. The data can be processed using the Kubios Heart Rate Variability Software.

Ideally, a future study could simultaneously collect sleep data, HRV data, and RF data among firefighters. This would allow for regressions to be conducted where accurate personal RF exposure was the predictor, and sleep quality and quantity as well as HRV were the outcomes.

Conclusion

It is possible to use publicly available data sets to systematically select fire stations with a range of urbanicity and a range of number of proximal cell towers. The source of proximal cell towers could be improved on to better represent the actual number of proximal cell towers. It is possible to sample these selected fire stations for low intensity RF exposure. The samples collected represented a plausible range of RF exposures among sampled fire stations. The results indicated that there is variance between fire stations as well as variation between outdoor and indoor samples. This indicated that fire stations' structure provides some level of RF shielding from outdoor exposures. It also indicates that some amount of RF is generated from within fire stations. The results collected were all well below the ICNIRP occupational guideline by a factor of 100 indicating that firefighters at the sampled fire stations are at no risk of tissue heating from RF exposure.

Our sampling device, the aaronia spectrum analyzer, has background RF that it detects in a theoretically RF free environment. This could be RF that the device itself is generating, or it could be specific frequencies that the Faraday bags used do a poor job shielding RF at. We collected a sample with our omnilog antennae within two of the Faraday bags, and saw similar results as when inside one Faraday bag, however this would be expected if both bags lacked shielding at certain frequencies.

The frequencies most contributing to the outdoor omnilog RF measurements collected at participating fire stations were 482.5-487.5MHz, and 5.8- 5.8105 GHZ. The frequencies most contributing to the outdoor hyperlog RF measurements were 739-770MHz, 839MHZ, 1.9575- 1.960GHZ, 5.8-5.8105GHz, 8.43-8.64GHz, and 8.86GHz- 9GHz. The frequencies most contributing to the indoor omnilog overnight RF samples were 320 MHz, 360 MHZ, 400 MHZ, and 5.8-5.8105GHz. It is hard to determine the sources of the RF exposure at these frequencies with complete certainty due to the overlapping frequency allocations set in place by the FCC (National Telecommunications and Information Administration, 2017). However, we conclude that the frequencies below 1 GHz are likely due to emergency services communications. The frequencies at and near 5.8GHz are likely due to Wi-Fi. The frequencies from 8.43GHz to 9GHz are likely from mobile phone towers. Our measurements showed variation between indoor and outdoor RF exposure at stations. This indicates that RF is being generated with the fire stations.

After analyzing the PSQI survey results, specifically the distribution of our created outcome, "six hours of sleep or less" which is used as an indicator of short sleep duration, we saw that 37 percent of our respondents get short sleep on average. This is in line with a national survey identifying that 38.2 percent of protective service workers get 6 hours of sleep or less on average (Luckhaupt et al., 2010a).

We were able to create multiple regressions with our data collected. One regression of interest is that an increase of nights on shift in the last month was statistically correlated with an increase in PSQI score, contributing to these individuals experiencing poorer sleeper. We did similar regressions using Nights on shift as the independent variable and PSQI component scores as the outcome variables for each component. These regressions were largely not statistically significant except for component 7, daytime dysfunction. Additionally, we were able to create regressions that used fire station RF measures as the independent variable, and PSQI scores at the outcome variable, with our limited data set and lack of personal exposure measures, these regressions were not statistically significant as one would expect with our limited data but show the regressions that can be performed in a future study with a more robust dataset.

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Appendix

import_xml function

```
import_xml <- function(datafilepath, antenna_type, getGPS = F) {
  #rda_path <- str_replace(datafilepath, ".mdr", ".rda")
  #if (! file.exists(rda_path)) {
    xmlfile <- read_xml(datafilepath)
    getGPS<-FALSE
    # xmldf <- xmlToDataFrame(nodes = getNodeSet(xmlfile,
"//Sweep/Values"))
    #
    # test = xmlToDataFrame(sweep[1])

    #get data structure
    xml_children((xml_children(xmlfile)[[5]]))

    #get measurement data
    frequencies <- xmlfile %>% xml_find_all(".//Frequencies")
    values <- xmlfile %>% xml_find_all(".//Values")

    #get header data
    calibdata <- as_list(xmlfile %>% xml_find_all(".//CalibrationData
"))
    device_settings <- as_list(xmlfile %>%
xml_find_all(".//DeviceSettings "))

    #get supporting data
    start <- unlist(as_list(xmlfile %>% xml_find_all(".//StartDate")))
    stop <- unlist(as_list(xmlfile %>% xml_find_all(".//StopDate")))
    latitude <- unlist(as_list(xmlfile %>%
xml_find_all(".//Latitude")))
    longitude  <- unlist(as_list(xmlfile %>% xml_find_all(".//Longitude
")))

    #convert_time
    start = with_tz(ymd_hms(start), "America/Los_Angeles")
    stop = with_tz(ymd_hms(stop), "America/Los_Angeles")

    additional_desc = data.table(start = start, stop = stop, latitude =
latitude, longitude = longitude)
    additional_desc[, sample := paste0("r", 1:length(start))]


    frequencies_list = lapply(1:length(frequencies), FUN = function(x){
      unlist(read.table(text =
unlist(unlist(as_list(frequencies[[x]]))), sep = ";"))
    })

    frequencies_list[duplicated(frequencies_list)] = NULL
```

```
    values_list = lapply(1:length(values), FUN = function(x){
      unlist(read.table(text = unlist(unlist(as_list(values[[x]]))),
sep = ";"))
    })


    bind_list = lapply(1: length(values_list), FUN = function(v)  {
      val = v
      lapply(frequencies_list, FUN = function (f)
      {
        if(length(values_list[[val]]) == length(f) )
        {
          return(cbind(frequency = f, value = values_list[[val]],
sample = paste0("r",val)))
        }
        return(NULL)
      })
    })

    bind_list1 = lapply(bind_list, FUN = function(x)
as.data.frame(x[[1]]))


    data_run = rbindlist(bind_list1)

    #add dates
    data_run$datetime <- as.POSIXct(unlist(lapply(1:length(bind_list),
FUN = function(x)
    {
      seq(from = additional_desc[x, start], to = additional_desc[x,
stop], length.out = nrow(bind_list1[[x]]))
    })), origin = "1970-01-01")

    #add longitude

    library(rgdal)

    #get degrees decimal

    if(getGPS == T){

      try(
        sputm <- SpatialPoints(cbind(longitude =
                                     #convert degrees longitude to
decimal longitude USE EYES

as.numeric(substr(additional_desc$longitude, 1, 4)) -

as.numeric(substr(additional_desc$longitude, 5,6))/60
                                     #as.numeric(sprintf("%3.2f",
as.numeric(substr(additional_desc$longitude, 7,9))))*100/3600
                                     ,
```

```
                                     #convert degrees latitude to
decimal latitude
                                     latitude =
as.numeric(substr(additional_desc$latitude, 1, 2)) +

as.numeric(substr(additional_desc$latitude, 3,4))/60 +
                                       as.numeric(sprintf("%3.2f",
as.numeric(substr(additional_desc$latitude, 5,7))))*100/3600) ,
                               proj4string =CRS("+proj=longlat
+datum=WGS84"))
      )

      try(
        sputm <- SpatialPoints(cbind(longitude =
                                       #convert degrees longitude to
decimal longitude USE EYES

as.numeric(substr(additional_desc$longitude, 1, 4)) -

as.numeric(substr(additional_desc$longitude, 5,6))/60 -

as.numeric(substr(sprintf("%.1f",
as.numeric(additional_desc$longitude)), 7,9))*100/3600 ,
                                     #convert degrees latitude to
decimal latitude
                                     latitude =
as.numeric(substr(sprintf("%.2f",
as.numeric(additional_desc$latitude)), 1, 2)) +

as.numeric(substr(additional_desc$latitude, 3,4))/60 +

as.numeric(substr(sprintf("%.2f",as.numeric(additional_desc$latitude)),
5,7))*100/3600) ,
                               proj4string =CRS("+proj=longlat
+datum=WGS84"))
      )



      spgeo <- spTransform(sputm, CRS("+proj=longlat +datum=WGS84"))

      lnlt <- coordinates(spgeo)


      data_run$longitude <- unlist(lapply(1:length(bind_list1), FUN =
function(x)
      {
        rep(lnlt[x, "longitude" ], length.out = nrow(bind_list1[[x]]))
      }))

      data_run$latitude <- unlist(lapply(1:length(bind_list1), FUN =
function(x)
```

```
      {
        rep(lnlt[x, "latitude" ], length.out = nrow(bind_list1[[x]]))
      }))

    }


    data_run[, frequency := as.numeric(frequency)]
    data_run[, value  := as.numeric(value )]
    data_run = data_run[!is.na(frequency),]




    #convert to w/m2 using Table 1 of the manual and the LambdaX column
as suggested. This must be adapted for antennae and such.
    conversion = fread("/projects/austinlab/R code for RF data
analysis/Unit_Conversion_Aaronia.csv")
    #antenna_type="omnilog"
    conversion[, dBm := as.numeric(dBm)]
    if(antenna_type=="omnilog"){

      conversion$dBm=conversion$dBm+2
    }

    conversion[, LambdaX := as.numeric(LambdaX)]


    #develop conversion formula
    lmwm2 = lm(log(LambdaX) ~ dBm, data = conversion)
    summary(lmwm2)

    data_run[, dBm := value]
    data_run[,dBm := as.numeric(dBm)]
    data_run[, w.m2 := exp(predict(lmwm2, data_run))]
    #convert to V/m (reference
https://www.aaronia.com/fileadmin/media-archive/conversion_formulas.pdf
)
    data_run[, v.m :=  sqrt(w.m2 * 377)]

    #add reference
https://journals.lww.com/health-physics/Fulltext/2020/05000/Guidelines_
for_Limiting_Exposure_to.2.aspx#T5

    #only using the 6th column since all the values measured are above
the 3000 Hz value
    data_run[, frequency:= as.numeric(as.character(frequency))]
    data_run[frequency > 100000 &
               frequency <= 30000000,
             percent.icnrp.pop :=
(v.m/(300/((frequency*10^(-6))^(0.7))))*100]
    data_run[frequency > 30000000 &
```

```
                frequency <= 400000000,
              percent.icnrp.pop:= (v.m/27.7)*100]

    data_run[frequency > 400000000 &
                frequency <= 2000000000,
              percent.icnrp.pop := (v.m/(1.375*
((frequency*10^(-6))*(0.5))))*100]

    data_run[frequency > 2000000000 &
                frequency < 300000000000,
              percent.icnrp.pop :=(w.m2/(10))*100] #convert from
incident power density to replace na

    #           Break for ocupational exposure comparison
    data_run[frequency > 100000 &
                frequency < 30000000,
              percent.icnrp.ocu :=
(v.m/(660/((frequency*10^(-6))^(0.7))))*100]

    data_run[frequency > 30000000 &
                frequency < 400000000,
              percent.icnrp.ocu:=(v.m/61)*100]

    data_run[frequency > 400000000 &
                frequency < 2000000000,
              percent.icnrp.ocu
:=(v.m/(3*((frequency*10^(-6))*(0.5))))*100]

    data_run[frequency > 2000000000 &
                frequency < 300000000000,
              percent.icnrp.ocu :=(w.m2/(50))*100] #convert from
incident power density to replace na


  return(data_run)
}
```

Process r data function:

```
library(pacman)
p_load(xml2, XML, tidyverse, data.table, ggplot2, ggridges, plyr,
lubridate)
Process_data <-
function(rfdata,station_name,Faraday_Limit_of_Detection,filename_top20,
filename_ggplot, filename_icnirp){
  setkey(rfdata,frequency)
  setkey(Faraday_Limit_of_Detection,frequency)
  rfdata=merge(rfdata,Faraday_Limit_of_Detection,all.x=T)

  #subset to match antennae range
  rfdata_subset<-subset(rfdata,frequency<=8000000000 &
frequency>=300000000)
```

```
  #compare subset to Faraday limit of detection

  #take median sweep
  #can add additional LOD columns
  rfdata_median_sweep<-rfdata_subset[,list(
    median_v.m=median(v.m,na.rm=T),
    median_w.m2=median(w.m2,na.rm=T),
    q95_v.m=quantile(v.m,0.95,na.rm=T),
    median_percent.icnrp.pop=median(percent.icnrp.pop,na.rm=T),
    median_percent.icnrp.ocu=median(percent.icnrp.ocu,na.rm=T),
    q95_percent.icnrp.pop=quantile(percent.icnrp.pop,0.95,na.rm=T),

q95_percent.icnrp.ocu=quantile(percent.icnrp.ocu,0.95,na.rm=T)),by=c("f
requency","LOD_background_v.m")]
  rfdata_median_sweep[,v.m_LOD:=median_v.m-LOD_background_v.m]

  p1=ggplot(rfdata_median_sweep, aes(x = frequency, y =median_v.m))+
    geom_line()+ geom_point(aes(x=frequency,y=LOD_background_v.m),
color="red",size=0.2) + xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")

  #plotting 95th percentile
  p2=ggplot(rfdata_median_sweep, aes(x = frequency, y =q95_v.m))+
    geom_line()+ geom_point(aes(x=frequency,y=LOD_background_v.m),
color="red",size=0.2)+ xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")

  ggsave(paste0(filename_ggplot, "_medianv_m.png"), p1)
  ggsave(paste0(filename_ggplot, "_q95v_m.png"), p2)

  #rfdata_median_sweep[median_v.m>0.2,]
  #from here we can pull out the frequencies with highest v.m,
eventually report %ICNIRP even though it is low
  rfdata_median_sweep$station_name=station_name

write.csv(rfdata_median_sweep[order(-median_v.m),][1:20,],filename_top2
0)
  #adding in new column subtracting LOD

  #rfdata_median_sweep[v.m_LOD>0,]
  p3 = ggplot(rfdata_median_sweep[v.m_LOD>0,],aes(x=frequency,
y=median_v.m))+geom_line()+ xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")


  ggsave(paste0(filename_ggplot, "above_lod_median_v_m.png"), p3)

  icnrp = data.frame(
    "max_median_icnrp.pop" =
max(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
```

```
    "min_median_icnrp.pop" =
min(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
    "sum_median_icnrp.pop" =
sum(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
    "max_q95_icnrp.pop" =
max(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
    "min_q95_icnrp.pop" =
min(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
    "sum_q95_icnrp.pop" =
sum(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
    "max_median_icnrp.ocu" =
max(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "min_median_icnrp.ocu" =
min(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "sum_median_icnrp.ocu" =
sum(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "max_q95_icnrp.ocu" =
max(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "min_q95_icnrp.ocu" =
min(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "sum_q95_icnrp.ocu" =
sum(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "station_name" = median(rfdata_median_sweep$station_name))

  write.csv(icnrp, filename_icnirp)
  return(rfdata_median_sweep)
}
```

Process hyperlog data function

```
library(pacman)
p_load(xml2, XML, tidyverse, data.table, ggplot2, ggridges, plyr,
lubridate)
Process_hyperlog_data <-
function(rfdata,station_name,Faraday_hyperlog_Limit_of_Detection,filena
me_top20,filename_ggplot, filename_icnirp){
  setkey(rfdata,frequency)
  setkey(Faraday_hyperlog_Limit_of_Detection,frequency)
  rfdata=merge(rfdata,Faraday_hyperlog_Limit_of_Detection,all.x=T)

  #subset to match antennae range
  rfdata_subset<-subset(rfdata,frequency>=680000000)


  #compare subset to Faraday limit of detection

  #take median sweep
  #can add additional LOD columns
  rfdata_median_sweep<-rfdata_subset[,list(
    median_v.m=median(v.m,na.rm=T),
    median_w.m2=median(w.m2,na.rm=T),
    q95_v.m=quantile(v.m,0.95,na.rm=T),
    median_percent.icnrp.pop=median(percent.icnrp.pop,na.rm=T),
```

```
    median_percent.icnrp.ocu=median(percent.icnrp.ocu,na.rm=T),
    q95_percent.icnrp.pop=quantile(percent.icnrp.pop,0.95,na.rm=T),

q95_percent.icnrp.ocu=quantile(percent.icnrp.ocu,0.95,na.rm=T)),by=c("f
requency","LOD_background_v.m")]
  rfdata_median_sweep[,v.m_LOD:=median_v.m-LOD_background_v.m]

  p1=ggplot(rfdata_median_sweep, aes(x = frequency, y =median_v.m))+
    geom_line()+ geom_point(aes(x=frequency,y=LOD_background_v.m),
color="red",size=0.2) + xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")

  #plotting 95th percentile
  p2=ggplot(rfdata_median_sweep, aes(x = frequency, y =q95_v.m))+
    geom_line()+ geom_point(aes(x=frequency,y=LOD_background_v.m),
color="red",size=0.2)+ xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")

  ggsave(paste0(filename_ggplot, "_medianv_m.png"), p1)
  ggsave(paste0(filename_ggplot, "_q95v_m.png"), p2)

  #rfdata_median_sweep[median_v.m>0.2,]
  #from here we can pull out the frequencies with highest v.m,
eventually report %ICNIRP even though it is low
  rfdata_median_sweep$station_name=station_name

write.csv(rfdata_median_sweep[order(-median_v.m),][1:20,],filename_top2
0)
  #adding in new column subtracting LOD

  #rfdata_median_sweep[v.m_LOD>0,]
  p3 = ggplot(rfdata_median_sweep[v.m_LOD>0,],aes(x=frequency,
y=median_v.m))+geom_line()+ xlab("Frequency (Hz)") +
    ylab("Electric Field Strength (V/m)")


  ggsave(paste0(filename_ggplot, "above_lod_median_v_m.png"), p3)

  icnrp = data.frame(
    "max_median_icnrp.pop" =
max(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
    "min_median_icnrp.pop" =
min(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
    "sum_median_icnrp.pop" =
sum(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.pop, na.rm=T),
    "max_q95_icnrp.pop" =
max(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
    "min_q95_icnrp.pop" =
min(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
    "sum_q95_icnrp.pop" =
sum(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.pop, na.rm=T),
```

```
    "max_median_icnrp.ocu" =
max(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "min_median_icnrp.ocu" =
min(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "sum_median_icnrp.ocu" =
sum(rfdata_median_sweep[v.m_LOD>0,]$median_percent.icnrp.ocu, na.rm=T),
    "max_q95_icnrp.ocu" =
max(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "min_q95_icnrp.ocu" =
min(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "sum_q95_icnrp.ocu" =
sum(rfdata_median_sweep[v.m_LOD>0,]$q95_percent.icnrp.ocu, na.rm=T),
    "station_name" = median(rfdata_median_sweep$station_name))

  write.csv(icnrp, filename_icnirp)
  return(rfdata_median_sweep)
}
```

Outdoor data analysis code:

```
library(pacman)
p_load(xml2, XML, tidyverse, data.table, ggplot2, plyr, lubridate)
#top 20 omnilog outdoor
station_46_top20<-read.csv("../outdoor_omnilog_data_outputs/Puget
Sound/Station 46/Station_46_top20.csv")
station_74_top20<-read.csv("../outdoor_omnilog_data_outputs/Puget
Sound/Station 74/Station_74_top20.csv")
station_75_top20<-read.csv("../outdoor_omnilog_data_outputs/Puget
Sound/Station 75/Station_75_top20.csv")
station_76_top20<-read.csv("../outdoor_omnilog_data_outputs/Puget
Sound/Station 76/Station_76_top20.csv")
station_80_top20<-read.csv("../outdoor_omnilog_data_outputs/Puget
Sound/Station 80/Station_80_top20.csv")
Renton_station_11_top20<-read.csv("../outdoor_omnilog_data_outputs/Rent
on/Station 11/Renton_Station_11_top20.csv")
station_12_top20<-read.csv("../outdoor_omnilog_data_outputs/Renton/Stat
ion 12/Station_12_top20.csv")
station_13_top20<-read.csv("../outdoor_omnilog_data_outputs/Renton/Stat
ion 13/Station_13_top20.csv")
station_16_top20<-read.csv("../outdoor_omnilog_data_outputs/Renton/Stat
ion 16/Station_16_top20.csv")
Renton_station_17_top20<-read.csv("../outdoor_omnilog_data_outputs/Rent
on/Station 17/Renton_Station_17_top20.csv")
Seattle_station_17_top20<-read.csv("../outdoor_omnilog_data_outputs/Sea
ttle/Station 17/Seattle_Station_17_top20.csv")
station_25_top20<-read.csv("../outdoor_omnilog_data_outputs/Seattle/Sta
tion 25/Station_25_top20.csv")
station_33_top20<-read.csv(
"../outdoor_omnilog_data_outputs/Seattle/Station
33/Station_33_top20.csv")
top_20_sum<-rbindlist(list(station_46_top20,station_74_top20,station_75
_top20,station_76_top20,station_80_top20,
```

```
Renton_station_11_top20,station_12_top20,station_13_top20,station_16_to
p20,Renton_station_17_top20,

Seattle_station_17_top20,station_25_top20,station_33_top20))
outdoor_top_20_omnilog_sum<-top_20_sum
write.csv(outdoor_top_20_omnilog_sum,"../results/outdoor_top_20_omnilog
_sum.csv")
ggplot(top_20_sum,aes(x=frequency,y=q95_v.m,color=station_name))+geom_p
oint()+
  labs(title="Top 20 Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quartile Intensity (v.m)")
#plot with anonymous stations
outdoor_top_20_omnilog_sum_anonymous<-read.csv("../results/outdoor_top_
20_omnilog_sum_anonymous.csv")
ggplot(outdoor_top_20_omnilog_sum_anonymous,aes(x=frequency,y=q95_v.m,c
olor=Anonymous_station_name))+geom_point()+
  labs(title="Top 20 Outdoor Omnilog Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quantile Intensity (v.m)")+
  scale_colour_discrete(name="Anonymous Station Names")
#top 20 hyperlog outdoor
station_46_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/P
uget Sound/Station 46/Station_46_hyperlog_top20.csv")
station_74_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/P
uget Sound/Station 74/Station_74_hyperlog_top20.csv")
station_75_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/P
uget Sound/Station 75/Station_75_hyperlog_top20.csv")
station_76_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/P
uget Sound/Station 76/Station_76_hyperlog_top20.csv")
station_80_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/P
uget Sound/Station 80/Station_80_hyperlog_top20.csv")
station_12_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/R
enton/Station 12/Station_12_hyperlog_top20.csv")
station_13_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/R
enton/Station 13/Station_13_hyperlog_top20.csv")
station_16_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/R
enton/Station 16/Station_16_hyperlog_top20.csv")
Renton_station_17_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_ou
tputs/Renton/Station 17/Station_17_hyperlog_top20.csv")
Seattle_station_17_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_o
utputs/Seattle/Station 17/Station_17_hyperlog_top20.csv")
station_25_hyperlog_top20<-read.csv("../outdoor_hyperlog_data_outputs/S
eattle/Station 25/Station_25_hyperlog_top20.csv")
station_33_hyperlog_top20<-read.csv(
"../outdoor_hyperlog_data_outputs/Seattle/Station
33/Station_33_hyperlog_top20.csv")
top_20_hyperlog_sum<-rbindlist(list(station_46_hyperlog_top20,station_7
4_hyperlog_top20,station_75_hyperlog_top20,

station_76_hyperlog_top20,station_80_hyperlog_top20,station_12_hyperlog
_top20,
```

```
station_13_hyperlog_top20,station_16_hyperlog_top20,Renton_station_17_h
yperlog_top20,

Seattle_station_17_hyperlog_top20,station_25_hyperlog_top20,station_33_
hyperlog_top20))

outdoor_top_20_hyperlog_sum<-top_20_hyperlog_sum
write.csv(outdoor_top_20_hyperlog_sum,"../results/outdoor_top_20_hyperl
og_sum.csv")
ggplot(top_20_hyperlog_sum,aes(x=frequency,y=q95_v.m,color=station_name
))+geom_point()+
  labs(title="Top 20 hyperlog Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quantile Intensity (v.m)")
#anonymous outdoor top 20 hyperlog sum plot
outdoor_top_20_hyperlog_sum_anonymous<-read.csv("../results/outdoor_top
_20_hyperlog_sum_anonymous.csv")
ggplot(outdoor_top_20_hyperlog_sum_anonymous,aes(x=frequency,y=q95_v.m,
color=Anonymous_station_name))+geom_point()+
  labs(title="Top 20 Outdoor Hyperlog Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quantile Intensity (v.m)")+
  scale_colour_discrete(name="Anonymous Station Names")
##############
#omnilog ICNIRP outdoor
station_46_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Pu
get Sound/Station 46/Station_46_ICNIRP_results.csv")
station_74_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Pu
get Sound/Station 74/Station_74_ICNIRP_results.csv")
station_75_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Pu
get Sound/Station 75/Station_75_ICNIRP_results.csv")
station_76_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Pu
get Sound/Station 76/Station_76_ICNIRP_results.csv")
station_80_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Pu
get Sound/Station 80/Station_80_ICNIRP_results.csv")
Renton_station_11_ICNIRP_results<-read.csv("../outdoor_omnilog_data_out
puts/Renton/Station 11/Renton_Station_11_ICNIRP_results.csv")
station_12_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Re
nton/Station 12/Station_12_ICNIRP_results.csv")
station_13_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Re
nton/Station 13/Station_13_ICNIRP_results.csv")
station_16_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Re
nton/Station 16/Station_16_ICNIRP_results.csv")
Renton_station_17_ICNIRP_results<-read.csv("../outdoor_omnilog_data_out
puts/Renton/Station 17/Renton_Station_17_ICNIRP_results.csv")
Seattle_station_17_ICNIRP_results<-read.csv("../outdoor_omnilog_data_ou
tputs/Seattle/Station 17/Seattle_Station_17_ICNIRP_results.csv")
station_25_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Se
attle/Station 25/Station_25_ICNIRP_results.csv")
station_33_ICNIRP_results<-read.csv("../outdoor_omnilog_data_outputs/Se
attle/Station 33/Station_33_ICNIRP_results.csv")
ICNIRP_results_sum<-rbindlist(list(station_46_ICNIRP_results,station_74
_ICNIRP_results,station_75_ICNIRP_results,
```

```
station_76_ICNIRP_results,station_80_ICNIRP_results,Renton_station_11_I
CNIRP_results,

station_12_ICNIRP_results,station_13_ICNIRP_results,station_16_ICNIRP_r
esults,

Renton_station_17_ICNIRP_results,Seattle_station_17_ICNIRP_results,

station_25_ICNIRP_results,station_33_ICNIRP_results))
#save as csv and add anonymous column
outdoor_ICNIRP_omnilog_sum<-ICNIRP_results_sum
write.csv(outdoor_ICNIRP_omnilog_sum,"../results/outdoor_ICNIRP_omnilog
_sum.csv")
outdoor_ICNIRP_omnilog_sum_anonymous<-read.csv("../results/outdoor_ICNI
RP_omnilog_sum_anonymous.csv")
ggplot(outdoor_ICNIRP_omnilog_sum_anonymous,aes(x=Anonymous_station_nam
e,y=sum_q95_icnrp.ocu))+geom_point()+
  labs(title="Outdoor Ommilog Percent of ICNIRP Occupational Guideline
by Station",
       x="Fire Station", y="95th Quantile sum Percent of ICNIRP
Occupational Guideline")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

#hyperlog ICNIRP outdoor
station_46_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Puget Sound/Station 46/Station_46_hyperlog_ICNIRP_results.csv")
station_74_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Puget Sound/Station 74/Station_74_hyperlog_ICNIRP_results.csv")
station_75_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Puget Sound/Station 75/Station_75_hyperlog_ICNIRP_results.csv")
station_76_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Puget Sound/Station 76/Station_76_hyperlog_ICNIRP_results.csv")
station_80_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Puget Sound/Station 80/Station_80_hyperlog_ICNIRP_results.csv")
station_12_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Renton/Station 12/Station_12_hyperlog_ICNIRP_results.csv")
station_13_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Renton/Station 13/Station_13_hyperlog_ICNIRP_results.csv")
station_16_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Renton/Station 16/Station_16_hyperlog_ICNIRP_results.csv")
Renton_station_17_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlo
g_data_outputs/Renton/Station
17/Station_17_hyperlog_ICNIRP_results.csv")
Seattle_station_17_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperl
og_data_outputs/Seattle/Station
17/Station_17_hyperlog_ICNIRP_results.csv")
station_25_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Seattle/Station 25/Station_25_hyperlog_ICNIRP_results.csv")
station_33_hyperlog_ICNIRP_results<-read.csv("../outdoor_hyperlog_data_
outputs/Seattle/Station 33/Station_33_hyperlog_ICNIRP_results.csv")
```

```
Hyperlog_ICNIRP_results_sum<-rbindlist(list(station_46_hyperlog_ICNIRP_
results,station_74_hyperlog_ICNIRP_results,

station_75_hyperlog_ICNIRP_results,station_76_hyperlog_ICNIRP_results,

station_80_hyperlog_ICNIRP_results,station_12_hyperlog_ICNIRP_results,

station_13_hyperlog_ICNIRP_results,station_16_hyperlog_ICNIRP_results,

Renton_station_17_hyperlog_ICNIRP_results,Seattle_station_17_hyperlog_I
CNIRP_results,

station_25_hyperlog_ICNIRP_results,station_33_hyperlog_ICNIRP_results))
#save as csv and anonymize
outdoor_ICNIRP_hyperlog_sum<-Hyperlog_ICNIRP_results_sum
write.csv(outdoor_ICNIRP_hyperlog_sum,"../results/outdoor_ICNIRP_hyperl
og_sum.csv")
outdoor_ICNIRP_hyperlog_sum_anonymous<-read.csv("../results/outdoor_ICN
IRP_hyperlog_sum_anonymous.csv")
ggplot(outdoor_ICNIRP_hyperlog_sum_anonymous,aes(x=Anonymous_station_na
me,y=sum_q95_icnrp.ocu))+geom_point()+
  labs(title="Outdoor Hyperlog Percent of ICNIRP Occupational Guideline
by Station",
       x="Fire Station", y="95th Quantile sum of Percent ICNIRP
Occupational limit")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))


ggplot(Hyperlog_ICNIRP_results_sum,aes(x=station_name,y=sum_q95_icnrp.o
cu))+geom_point()+
  labs(title="Hyperlog ICNIRP %Ocupational Limits by Station",
       x="Fire Station", y="95th Quartile sum ICNIRP Ocu Limit")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```

Indoor Data processing code:

```
library(pacman)
p_load(xml2, XML, tidyverse, data.table, ggplot2, ggridges, plyr,
lubridate)
#top 20 omnilog
Puget_Sound_station_46_indoor_top20<-read.csv("../indoor_omnilog_data_outpu
ts/Puget Sound/Station 46/Station_46_top20.csv")
Puget_Sound_station_74_indoor_top20<-read.csv("../indoor_omnilog_data_outpu
ts/Puget Sound/Station 74/Station_74_top20.csv")
Puget_Sound_station_75_indoor_top20<-read.csv("../indoor_omnilog_data_outpu
ts/Puget Sound/Station 75/Station_75_top20.csv")
Puget_Sound_station_76_indoor_top20<-read.csv("../indoor_omnilog_data_outpu
ts/Puget Sound/Station 76/Station_76_top20.csv")
Puget_Sound_station_80_indoor_top20<-read.csv("../indoor_omnilog_data_outpu
ts/Puget Sound/Station 80/Station_80_top20.csv")
Renton_station_11_indoor_top20<-read.csv("../indoor_omnilog_data_outputs/Re
nton/Station 11/Station_11_top20.csv")
```

```
Renton_station_12_indoor_top20<-read.csv("../indoor_omnilog_data_outputs/Re
nton/Station 12/Station_12_top20.csv")
Renton_station_13_indoor_top20<-read.csv("../indoor_omnilog_data_outputs/Re
nton/Station 13/Station_13_top20.csv")
Renton_station_16_indoor_top20<-read.csv("../indoor_omnilog_data_outputs/Re
nton/Station 16/Station_16_top20.csv")
Renton_station_17_indoor_top20<-read.csv("../indoor_omnilog_data_outputs/Re
nton/Station 17/Station_17_top20.csv")
indoor_top_20_sum<-rbindlist(list(Puget_Sound_station_46_indoor_top20,Puget
_Sound_station_74_indoor_top20,

Puget_Sound_station_75_indoor_top20,Puget_Sound_station_76_indoor_top20,

Puget_Sound_station_80_indoor_top20,Renton_station_11_indoor_top20,

Renton_station_12_indoor_top20,Renton_station_13_indoor_top20,

Renton_station_16_indoor_top20,Renton_station_17_indoor_top20))
#save as csv and anonymize
indoor_top_20_omnilog_sum<-indoor_top_20_sum
write.csv(indoor_top_20_omnilog_sum,"../results/indoor_top_20_omnilog_sum.c
sv")
indoor_top_20_omnilog_sum_anonymous<-read.csv("../results/indoor_top_20_omn
ilog_sum_anonymous.csv")

ggplot(indoor_top_20_omnilog_sum_anonymous,aes(x=frequency,y=q95_v.m,color=
Anonymous_station_name))+geom_point()+
  labs(title="Top 20 Indoor Omnilog Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quantile Intensity (v.m)")+
  scale_colour_discrete(name="Anonymous Station Names")


ggplot(indoor_top_20_sum,aes(x=frequency,y=q95_v.m,color=station_name))+geo
m_point()+
  labs(title="Top 20 Indoor Rf Intensities by Station",
       x="Frequency (Hertz)", y="95th Quartile Intensity (v.m)")
## Omnilog ICNIRP
Puget_Sound_station_46_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_d
ata_outputs/Puget Sound/Station 46/Station_46_ICNIRP_results.csv")
Puget_Sound_station_74_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_d
ata_outputs/Puget Sound/Station 74/Station_74_ICNIRP_results.csv")
Puget_Sound_station_75_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_d
ata_outputs/Puget Sound/Station 75/Station_75_ICNIRP_results.csv")
Puget_Sound_station_76_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_d
ata_outputs/Puget Sound/Station 76/Station_76_ICNIRP_results.csv")
Puget_Sound_station_80_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_d
ata_outputs/Puget Sound/Station 80/Station_80_ICNIRP_results.csv")
Renton_station_11_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_data_o
utputs/Renton/Station 11/Station_11_ICNIRP_results.csv")
Renton_station_12_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_data_o
utputs/Renton/Station 12/Station_12_ICNIRP_results.csv")
```

```
Renton_station_13_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_data_o
utputs/Renton/Station 13/Station_13_ICNIRP_results.csv")
Renton_station_16_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_data_o
utputs/Renton/Station 16/Station_16_ICNIRP_results.csv")
Renton_station_17_indoor_ICNIRP_results<-read.csv("../indoor_omnilog_data_o
utputs/Renton/Station 17/Station_17_ICNIRP_results.csv")
Indoor_ICNIRP_results_sum<-rbindlist(list(Puget_Sound_station_46_indoor_ICN
IRP_results,Puget_Sound_station_74_indoor_ICNIRP_results,

Puget_Sound_station_75_indoor_ICNIRP_results,Puget_Sound_station_76_indoor_
ICNIRP_results,

Puget_Sound_station_80_indoor_ICNIRP_results,Renton_station_11_indoor_ICNIR
P_results,

Renton_station_12_indoor_ICNIRP_results,Renton_station_13_indoor_ICNIRP_res
ults,

Renton_station_16_indoor_ICNIRP_results,Renton_station_17_indoor_ICNIRP_res
ults))


#case as csv and anonymize
Indoor_ICNIRP_omnilog_results_sum<-Indoor_ICNIRP_results_sum
write.csv(Indoor_ICNIRP_omnilog_results_sum,"../results/Indoor_ICNIRP_omnil
og_results_sum_anonymous.csv")
indoor_ICNIRP_omnilog_sum_anonymous<-read.csv("../results/Indoor_ICNIRP_omn
ilog_results_sum_anonymous.csv")


ggplot(indoor_ICNIRP_omnilog_sum_anonymous,aes(x=Anonymous_station_name,y=s
um_q95_icnrp.ocu))+geom_point()+
  labs(title="Indoor ICNIRP Omnilog Occupational Guideline by Station",
       x="Fire Station", y="95th Quantile sum of Percent ICNIRP
Occupational Guideline")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))


ggplot(Indoor_ICNIRP_results_sum,aes(x=station_name,y=sum_q95_icnrp.ocu))+g
eom_point()+
  labs(title="Indoor ICNIRP Ocupational Limits by Station",
       x="Fire Station", y="95th Quartile sum of Percent ICNIRP Ocupational
Guideline")+
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
```

lm(psqi_score~nights_on_shift_bins*less_6_sleep, data = datar) diagnostic plots

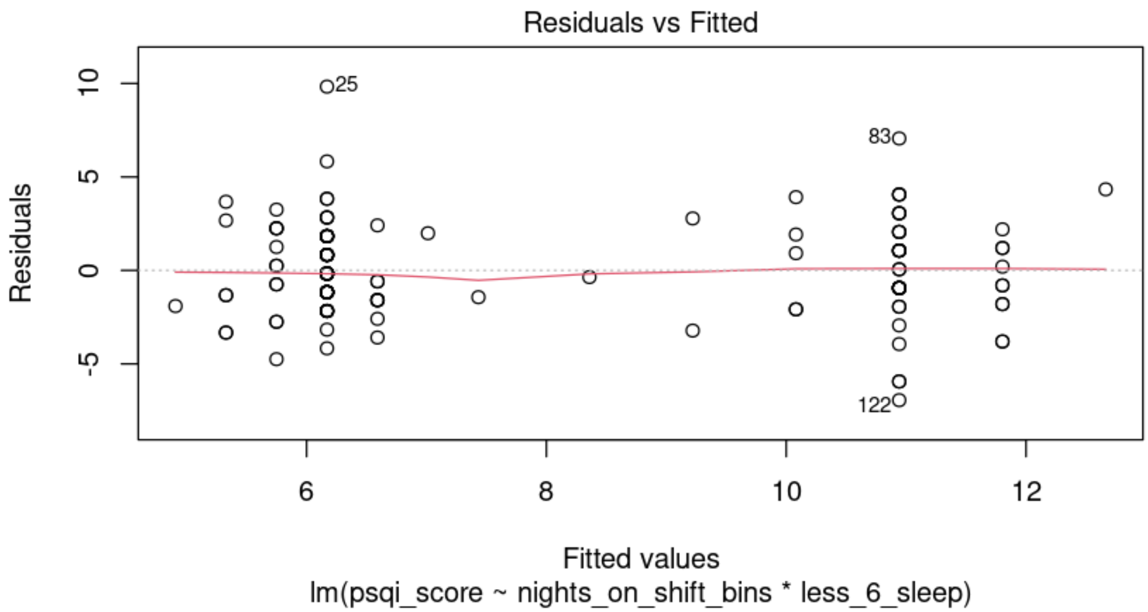

Figure 25. PSQI vs nights on shift binned and less 6 sleep residuals vs fitted

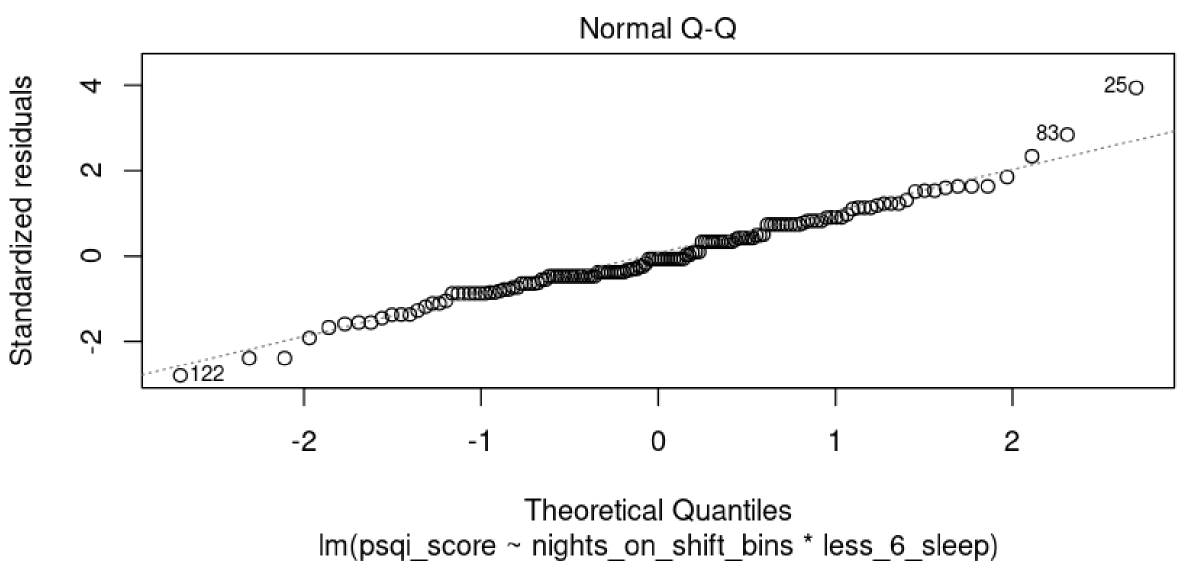

Figure 26. PSQI vs nights on shift binned and less 6 sleep normal Q-Q

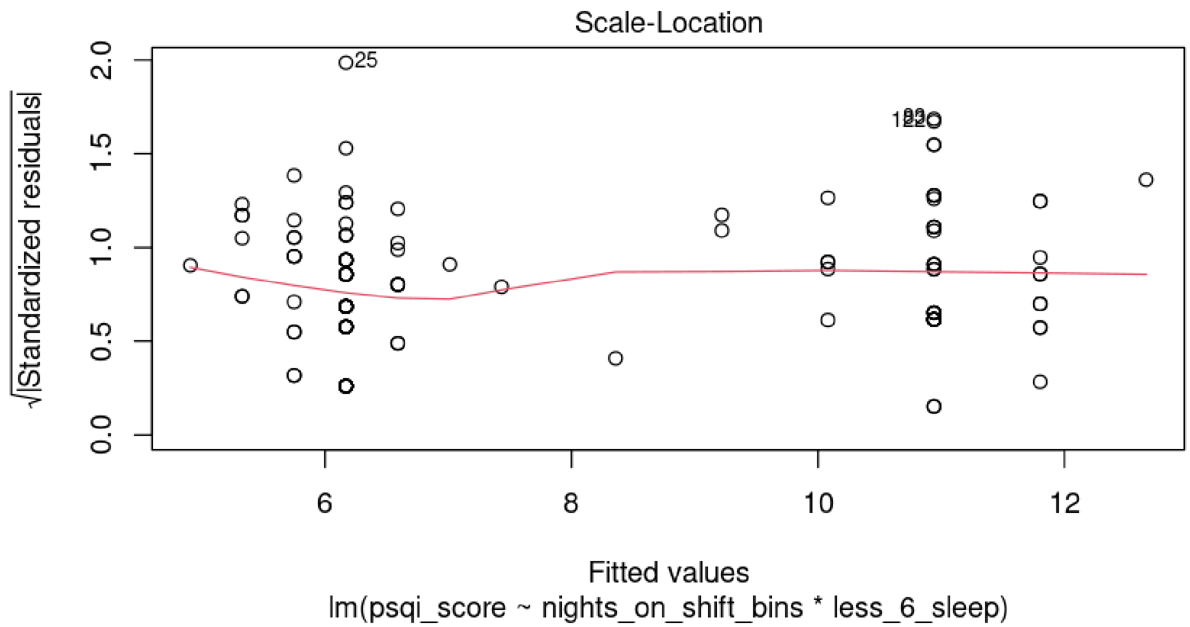

Figure 27. PSQI vs nights on shift binned and less 6 sleep Scale location

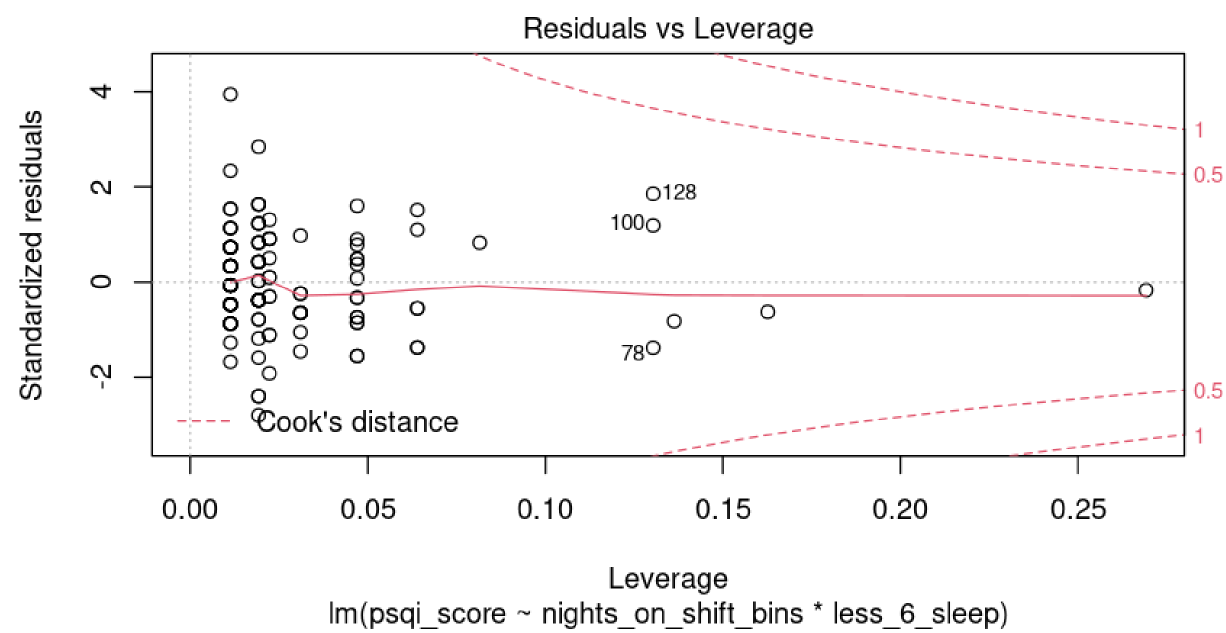

Figure 28. PSQI vs nights on shift binned and less 6 sleep influential points

Additive model PSQI~ nights on shift binned to multiples of 3+less than 6 hours of sleep Diagnostic plots

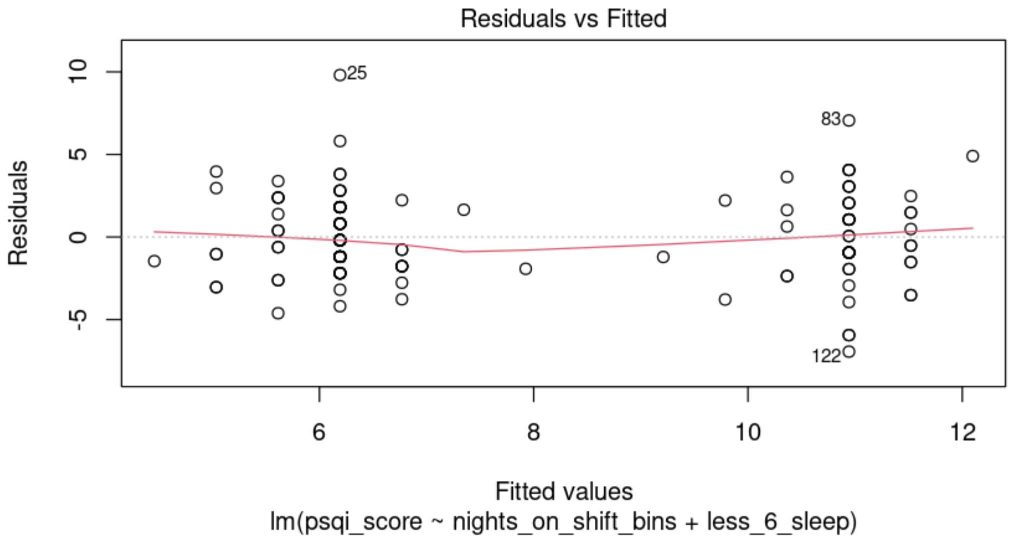

Figure 29. PSQI score by nights on shift binned plus less 6 sleep residuals vs fitted

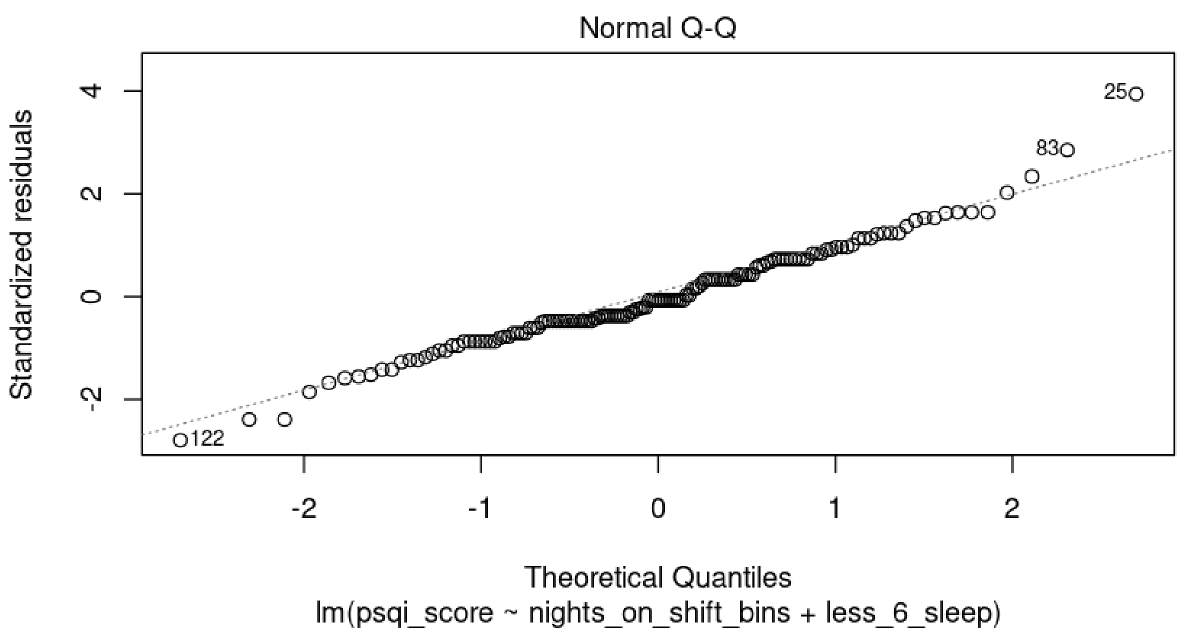

Figure 30. PSQI score by nights on shift binned plus less 6 sleep normal q-q

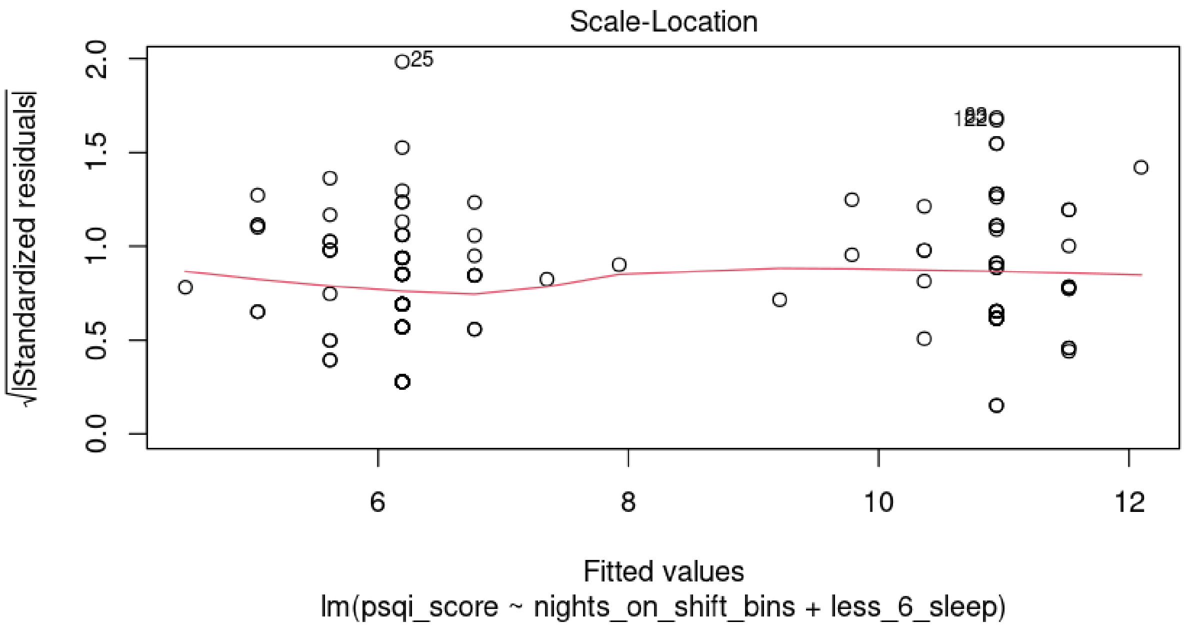

Figure 31. PSQI score by nights on shift binned plus less 6 sleep scale location

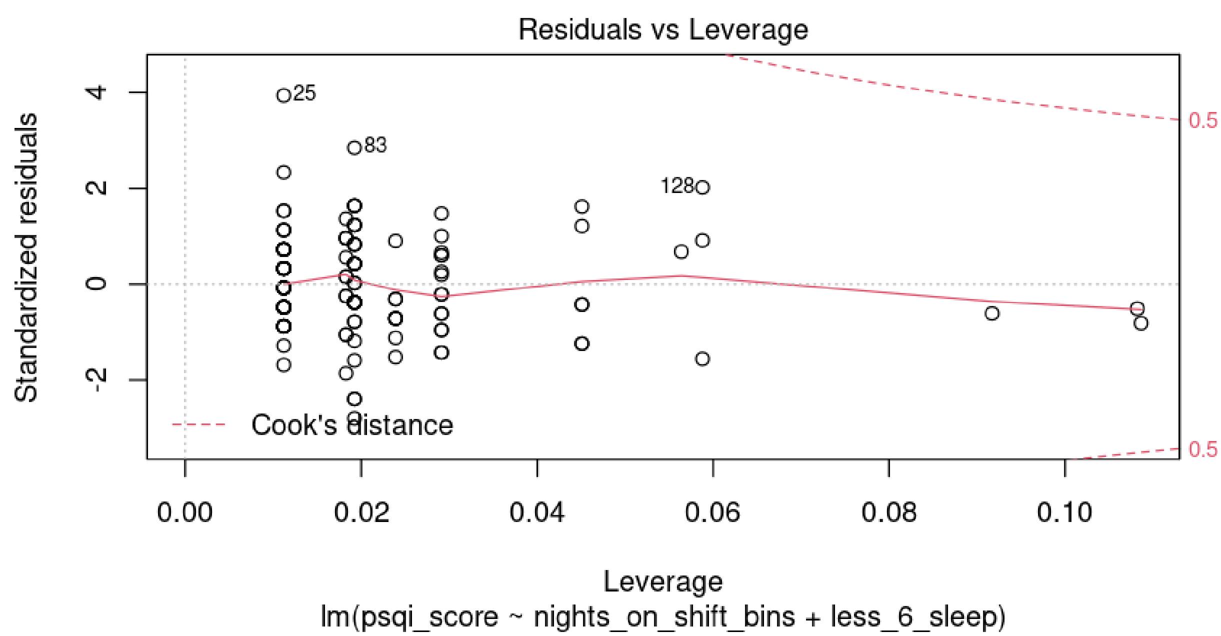

Figure 32. PSQI score by nights on shift binned plus less 6 sleep influential points

PSQI Component Boxplots by Anonymous Fire Station

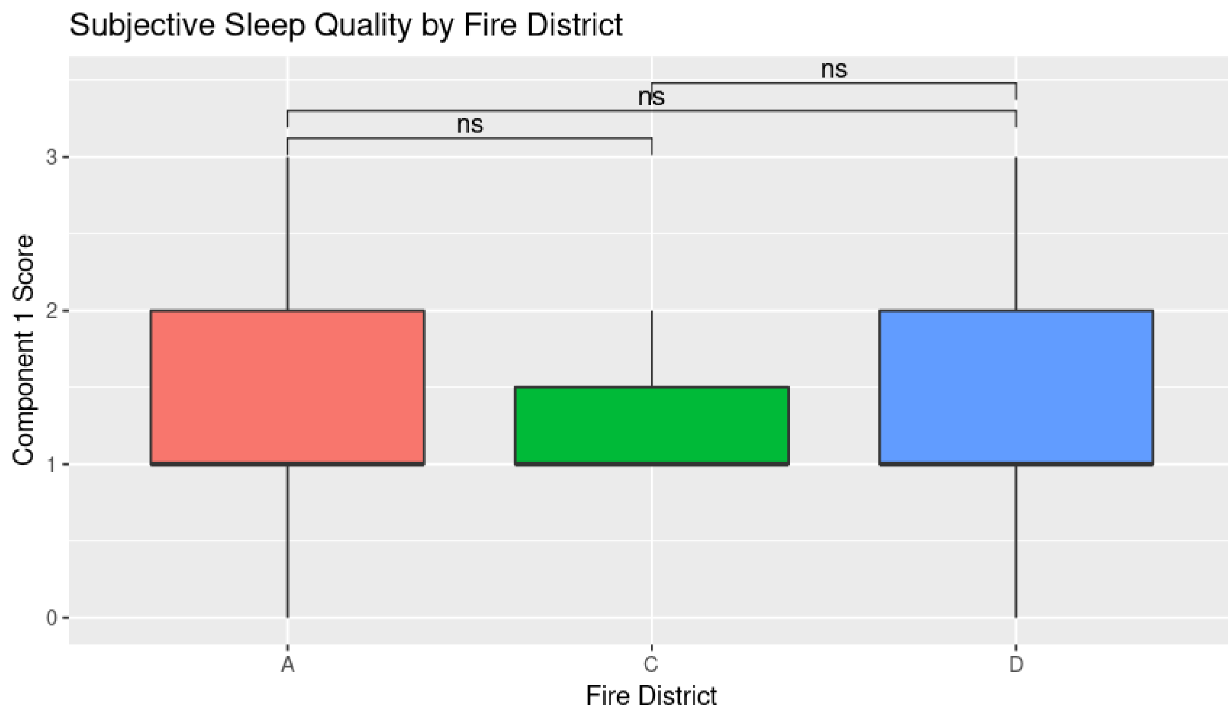

Figure 33. Component 1 subjective sleep quality boxplot by anonymous fire district

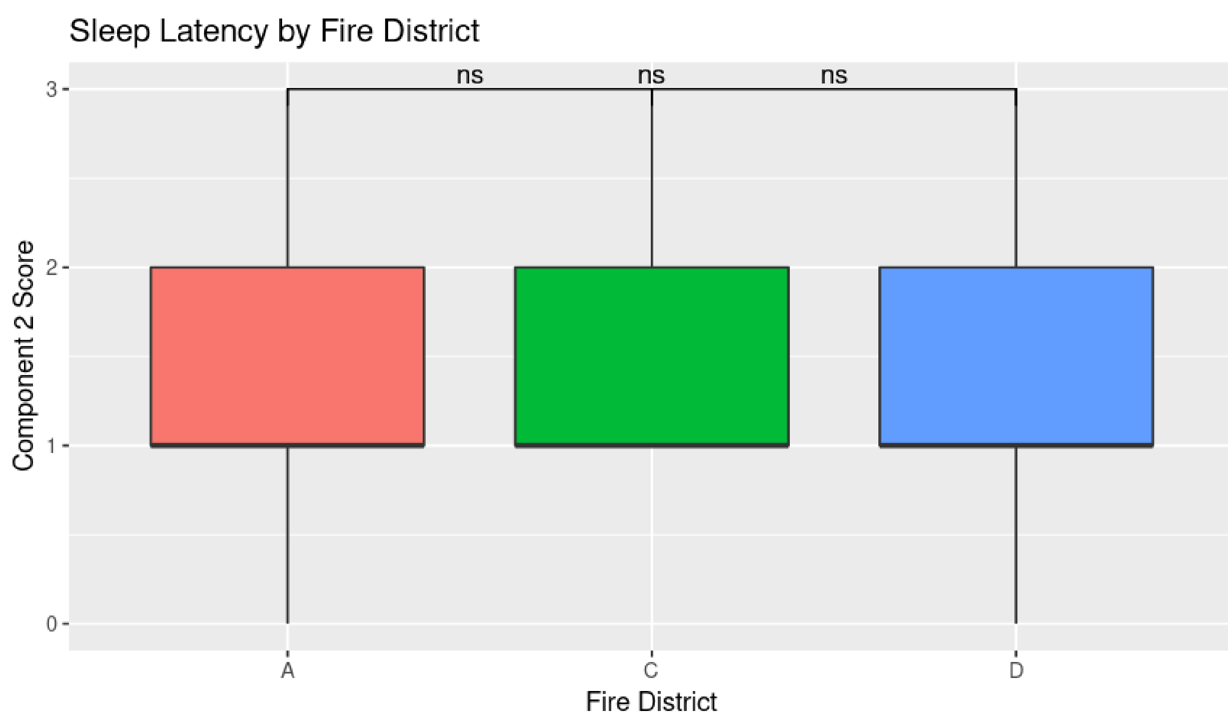

Figure 34. Component 2 Sleep Latency by Anonymous Fire District

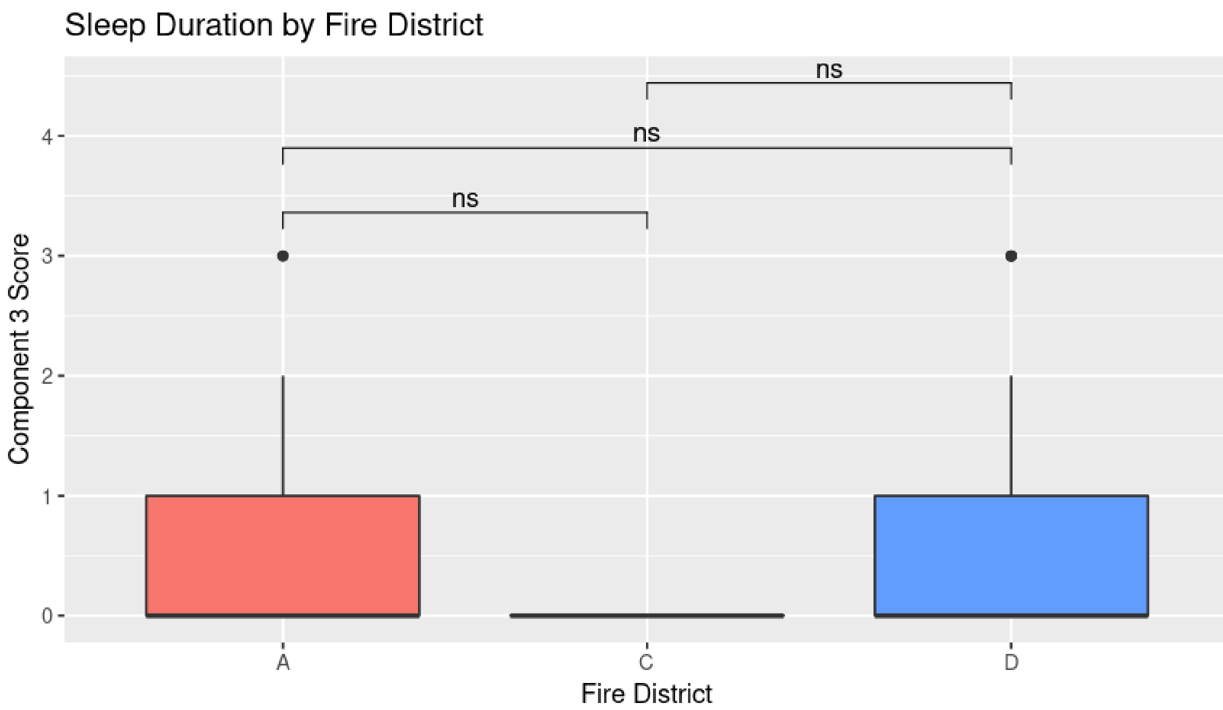

Figure 35. Component 3 sleep duration by anonymous fire district

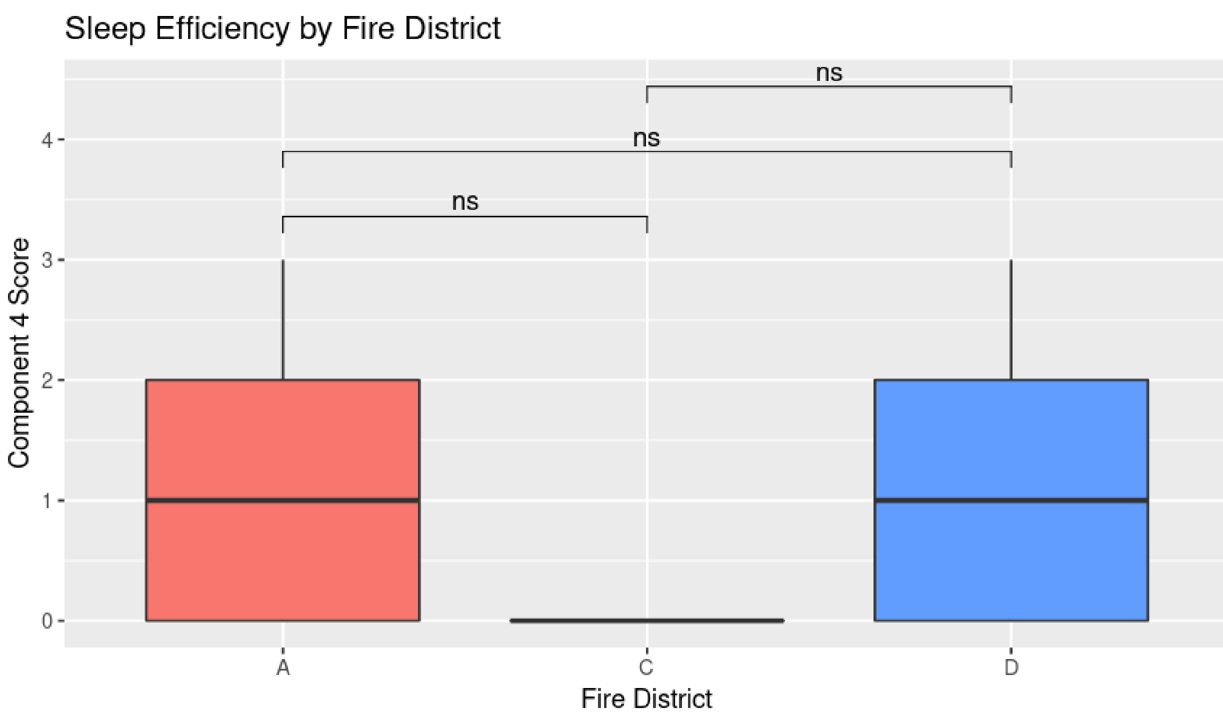

Figure 36. Component 4 sleep efficiency by anonymous fire district

Figure 37. Component 5 sleep disturbance by anonymous fire district

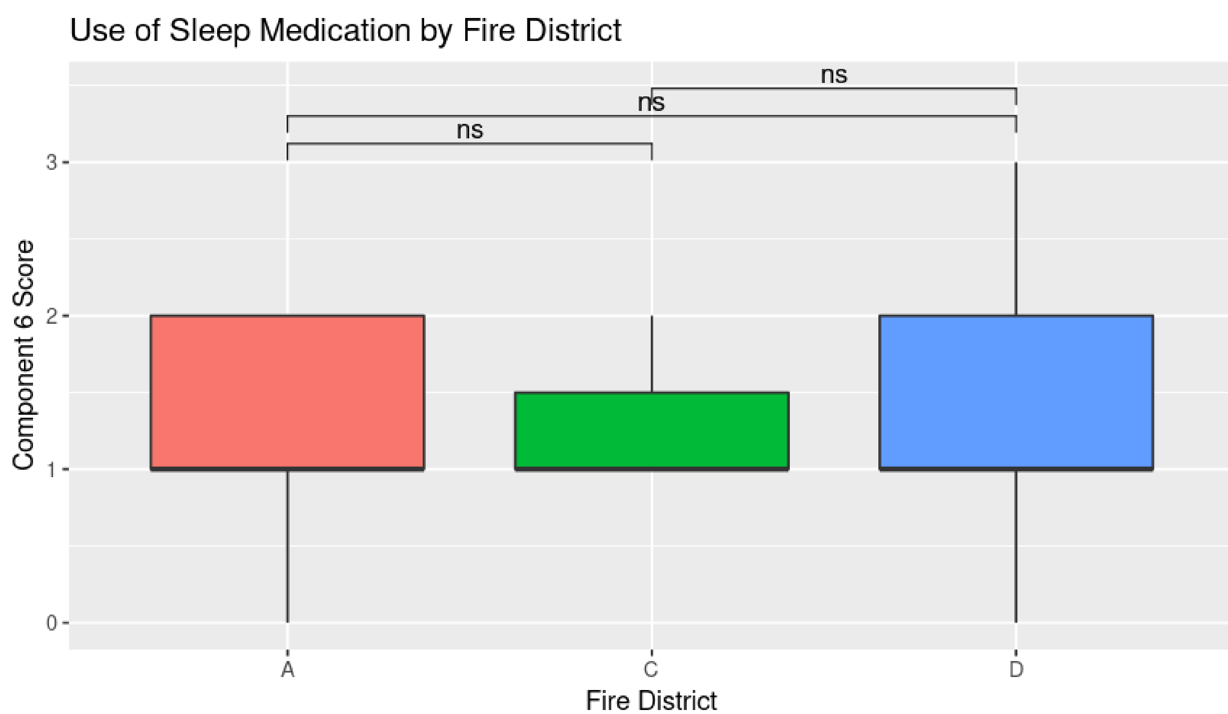

Figure 38. Component 6 use of sleep medication by anonymous fire district

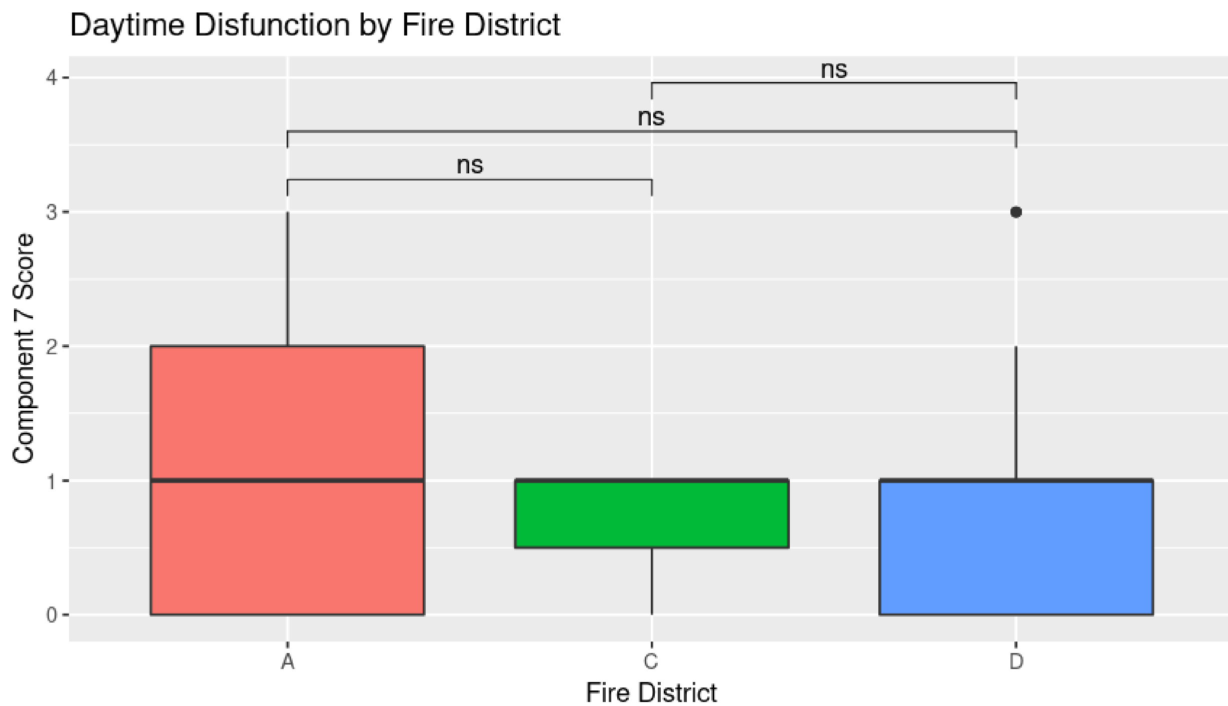

Figure 39. Component 7, daytime dysfunction by anonymous fire district

PSQI Nights on Shift Binned to nearest multiple of 3 vs PSQI Component scores

Figure 40. subjective sleep quality scores by nights on shift in the last month binned to the nearest multiple of 3

Regression summary:

```
Call:
lm(formula = Comp1 ~ nights_on_shift_bins, data = datar)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.4923 -0.3423 -0.3423  0.6577  1.6577 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           0.89231    0.24150   3.695 0.000314 ***
nights_on_shift_bins  0.05000    0.02658   1.881 0.061986 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.8045 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.02449,	Adjusted R-squared:  0.01757 
F-statistic: 3.539 on 1 and 141 DF,  p-value: 0.06199
```

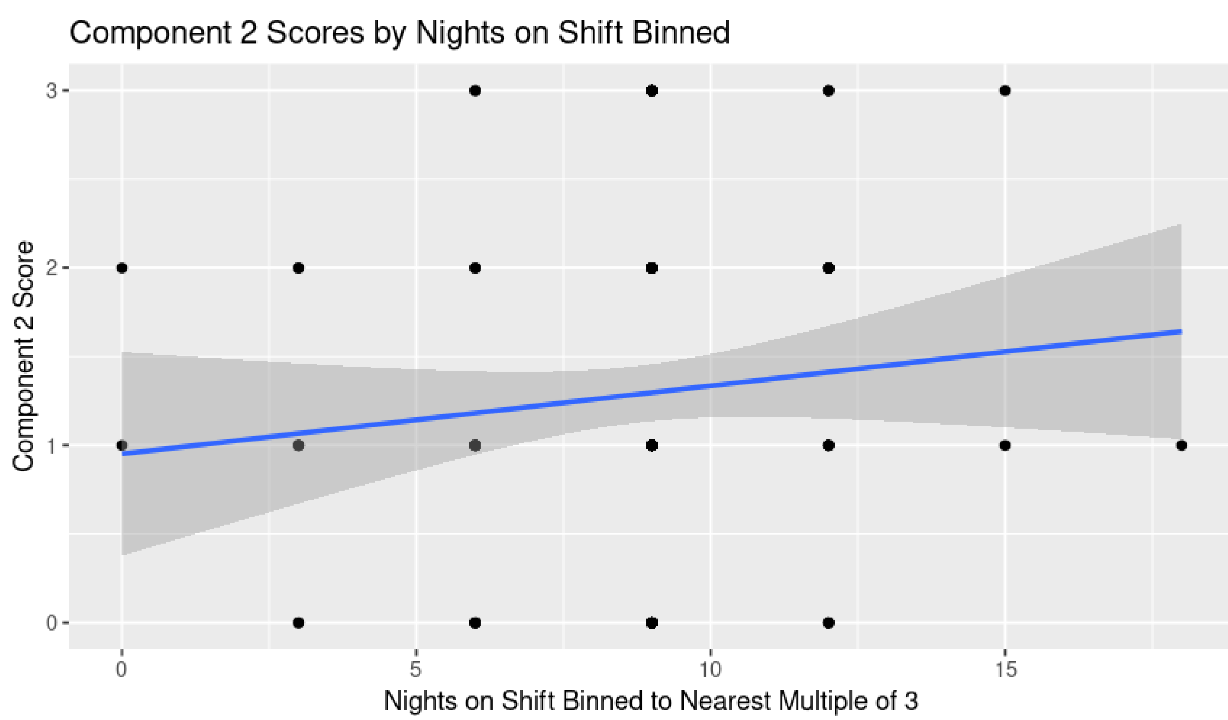

Figure 41. sleep latency scores by nights on shift in the last month binned to the nearest multiple of 3

Regression summary

```
lm(formula = Comp2 ~ nights_on_shift_bins, data = datar)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-1.4124 -0.4124 -0.2972  0.7028  1.8180 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)   
(Intercept)           0.95165    0.29033   3.278  0.00132 **
nights_on_shift_bins  0.03839    0.03195   1.202  0.23151   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.9672 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.01014,	Adjusted R-squared:  0.003117 
F-statistic: 1.444 on 1 and 141 DF,  p-value: 0.2315
```

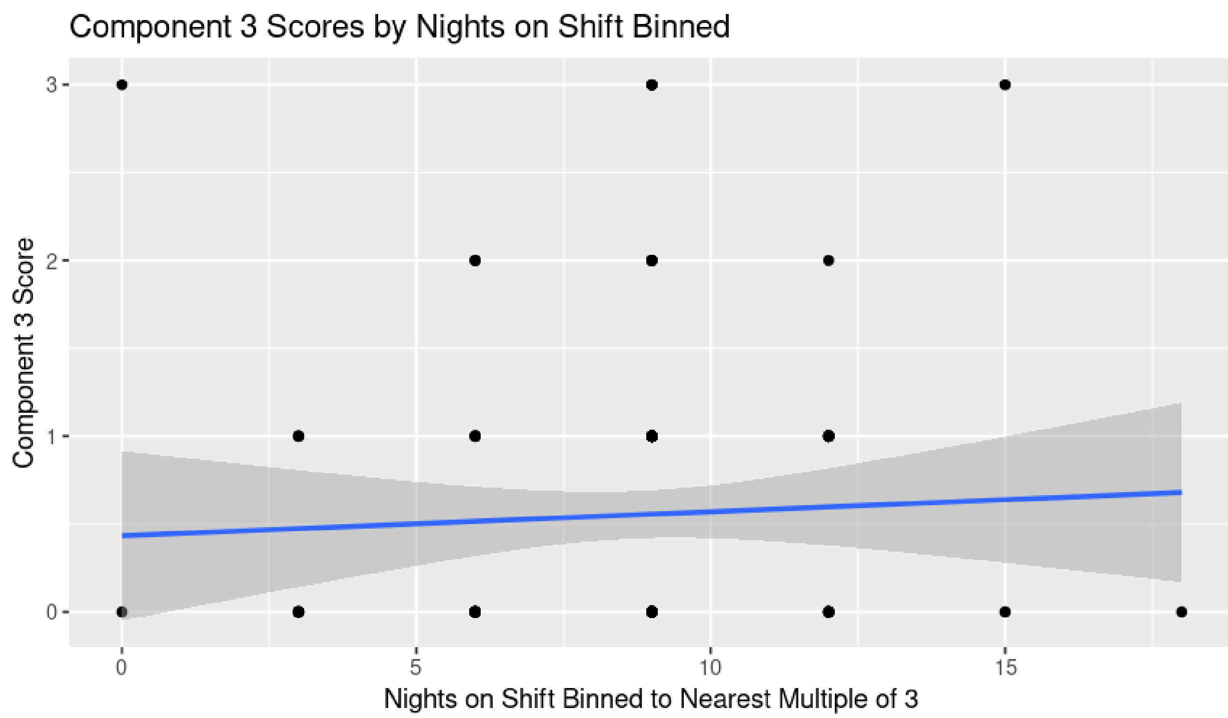

Figure 42. Sleep duration by nights on shift in the last month binned to the nearest multiple of 3

Regression summary –:

```
Call:
lm(formula = Comp3 ~ nights_on_shift_bins, data = datar)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.6794 -0.5562 -0.5151  0.4438  2.5670 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)           0.43297    0.24403   1.774   0.0782 .
nights_on_shift_bins  0.01369    0.02686   0.510   0.6110
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8129 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.00184,   Adjusted R-squared:  -0.005239
F-statistic: 0.2599 on 1 and 141 DF,  p-value: 0.611
```

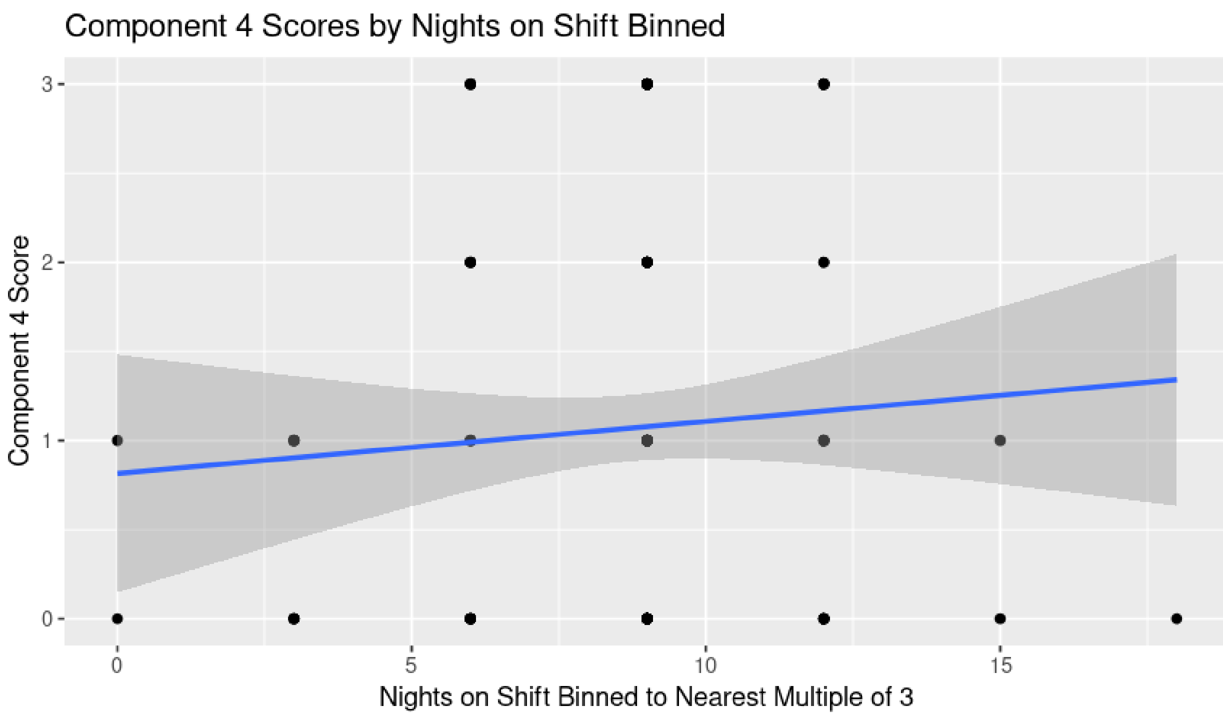

Figure 43. Sleep efficiency by nights on shift in the last month binned to the nearest multiple of 3

Regression summary:

```
Call:
lm(formula = Comp4 ~ nights_on_shift_bins, data = datar)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.34038 -1.07788 -0.07788  0.92212  2.00962 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)  
(Intercept)           0.81538    0.33777   2.414   0.0171 *
nights_on_shift_bins  0.02917    0.03717   0.785   0.4340  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.125 on 141 degrees of freedom
  (1 observation deleted due to missingness)
```

```
Multiple R-squared:  0.004348,	Adjusted R-squared:  -0.002714 
F-statistic: 0.6157 on 1 and 141 DF,  p-value: 0.434
```

Figure 44. Sleep disturbance by nights on shift in the last month binned to the nearest multiple of 3

Regression summary:

```
Call:
lm(formula = Comp5 ~ nights_on_shift_bins, data = datar)

Residuals:
    Min      1Q  Median      3Q     Max 
-0.7337 -0.4899 -0.3274  0.5101  1.5101 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           1.24615    0.15794   7.890  7.6e-13 ***
nights_on_shift_bins  0.02708    0.01738   1.558    0.121    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.5262 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.01693,	Adjusted R-squared:  0.009956 
F-statistic: 2.428 on 1 and 141 DF,  p-value: 0.1214
```

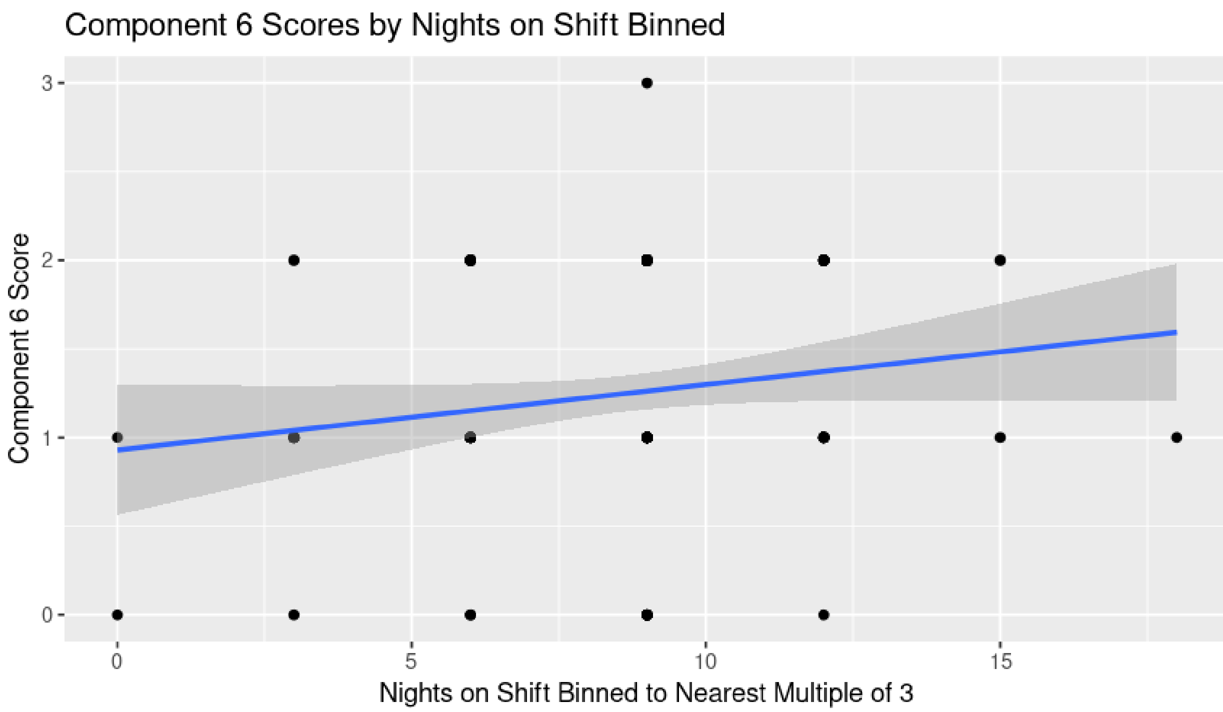

Figure 45. Use of sleep medication by nights on shift in the last month binned to the nearest multiple of 3

Regression summary:

```
Call:
lm(formula = Comp6 ~ nights_on_shift_bins, data = datar)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.3725 -0.2618 -0.2618  0.7382  1.7382 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)           0.92967    0.18523   5.019 1.54e-06 ***
nights_on_shift_bins  0.03690    0.02038   1.810   0.0724 .  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6171 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.02272,	Adjusted R-squared:  0.01579 
F-statistic: 3.278 on 1 and 141 DF,  p-value: 0.07236
```

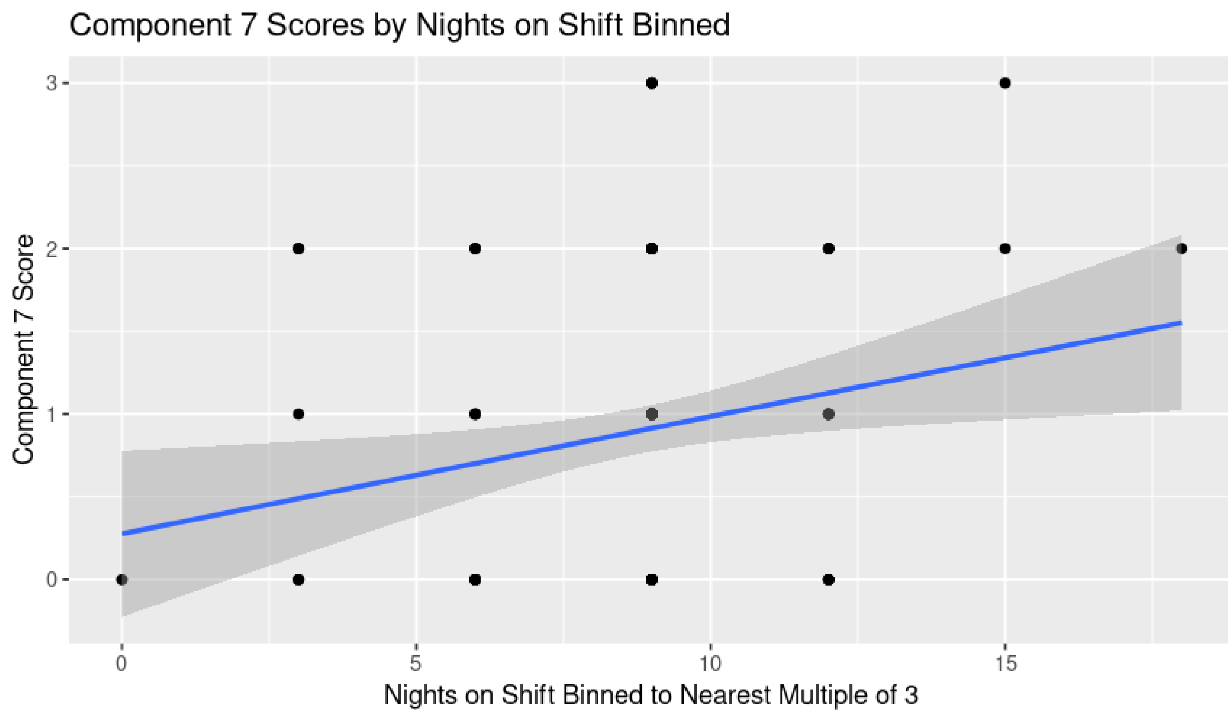

Figure 46. Daytime dysfunction by nights on shift in the last month binned to the nearest multiple of 3

Regression summary:

```
Call:
lm(formula = Comp7 ~ nights_on_shift_bins, data = datar)

Residuals:
     Min       1Q   Median       3Q      Max 
-1.12692 -0.91442  0.08558  0.29808  2.08558 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)  
(Intercept)           0.27692    0.25385   1.091   0.2772  
nights_on_shift_bins  0.07083    0.02794   2.536   0.0123 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.8456 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.04361,	Adjusted R-squared:  0.03683 
F-statistic:  6.43 on 1 and 141 DF,  p-value: 0.01231
```

PSQI Scoring Function

```
score_PSQI <- function(data){

  data$Comp1 <- rep(NA,nrow(data))
```

```
data$Comp2 <- rep(NA,nrow(data))
data$Comp3 <- rep(NA,nrow(data))
data$Comp4 <- rep(NA,nrow(data))
data$Comp5 <- rep(NA,nrow(data))
data$Comp6 <- rep(NA,nrow(data))
data$Comp7 <- rep(NA,nrow(data))

###Component 1###
data$Comp1 <- data$psqi_9_v2

###Component 2###
Score2 <- rep(NA,nrow(data))
Score2[data$psqi_2_v2<=15] <- 0
Score2[data$psqi_2_v2>15 & data$psqi_2_v2<=30] <- 1
Score2[data$psqi_2_v2>30 & data$psqi_2_v2<=60] <- 2
Score2[data$psqi_2_v2>60] <- 3

Score_Comp2 <- Score2 + data$psqi_5a_v2

data$Comp2[Score_Comp2==0] <- 0
data$Comp2[Score_Comp2==1 | Score_Comp2==2] <- 1
data$Comp2[Score_Comp2==3 | Score_Comp2==4] <- 2
data$Comp2[Score_Comp2==5 | Score_Comp2==6] <- 3

###Component 3###
data$Comp3[data$psqi_4_v2>=7] <- 0
data$Comp3[data$psqi_4_v2>=6 & data$psqi_4_v2<7] <- 1
data$Comp3[data$psqi_4_v2>=5 & data$psqi_4_v2<6] <- 2
data$Comp3[data$psqi_4_v2<5] <- 3

###Component 4###
risetime_hour = parse_date_time(paste("2022-07-19", datar$psqi_3_v2), order =
"%Y%m% d%H%M", tz = "America/Los_Angeles")
```

```
  bedtime_hour = parse_date_time(paste("2022-07-18", datar$psqi_1_v2), order = "%Y%m%
d%H%M", tz = "America/Los_Angeles")

#  bedtime_hour = parse_date_time(paste("2022-07-19", hour(datar$psqi_1_v2)<12),
order = "%Y%m% d%H%M", tz = "America/Los_Angeles")


#  bedtime_hour[bedtime_hour<12]=date(paste("2022-07-19"))

#  bedtime_hour = parse_date_time(paste("2022-07-19", hour(datar$psqi_1_v2<12:00)),
order = "%Y%m% d%H%M", tz = "America/Los_Angeles")

 bedtime_hour[hour(bedtime_hour)<12  &
!is.na(bedtime_hour),bedtime_hour:=bedtime_hour+(24*60*60)]

  #bedtime_hour[hour(bedtime_hour)<12 & hour(bedtime_hour)>4 & !is.na(bedtime_hour)
]+12*60*60


  Hours_in_Bed<- as.numeric(risetime_hour - bedtime_hour)

  Hours_in_Bed[Hours_in_Bed>24] = NA

  #Hours_in_Bed[Hours_in_Bed>24] = hour(Hours_in_Bed-24)

  Score_Comp4 <- rep(NA,nrow(data))

  Score_Comp4 <- data$psqi_4_v2/Hours_in_Bed*100

  data$Comp4[Score_Comp4 >= 85] <- 0

  data$Comp4[Score_Comp4 >= 75 & Score_Comp4 < 85] <- 1

  data$Comp4[Score_Comp4 >= 65 & Score_Comp4 < 75] <- 2

  data$Comp4[Score_Comp4 < 65] <- 3


  ###Component 5###

  data$psqi_5othera_v2[is.na(data$psqi_5othera_v2) | data$psqi_5othera_v2==""] <- 1

  Score_Comp5 <- data$psqi_5b_v2 + data$psqi_5c_v2 + data$psqi_5d_v2 +
data$psqi_5e_v2 + data$psqi_5f_v2 + data$psqi_5g_v2 + data$psqi_5h_v2 +
data$psqi_5i_v2 + data$psqi_5othera_v2

  data$Comp5[Score_Comp5 == 0] <- 0

  data$Comp5[Score_Comp5 >= 1 & Score_Comp5 <= 9] <- 1

  data$Comp5[Score_Comp5 >= 10 & Score_Comp5 <= 18] <- 2

  data$Comp5[Score_Comp5 >= 19 & Score_Comp5 <= 27] <- 3


  ###Component 6###

  data$Comp6 <- data$psqi_6_v2
```

```
  ###Component 7###
  Score_Comp7 <- data$psqi_7_v2  + data$psqi_8_v2
  data$Comp7[Score_Comp7==0] <- 0
  data$Comp7[Score_Comp7==1 | Score_Comp7==2] <- 1
  data$Comp7[Score_Comp7==3 | Score_Comp7==4] <- 2
  data$Comp7[Score_Comp7==5 | Score_Comp7==6] <- 3


  data$PSQI <- data$Comp1 + data$Comp2 + data$Comp3 + data$Comp4 + data$Comp5 +
data$Comp6 + data$Comp7
  #Creating PSQI>5 variable
  return(data$PSQI)
}
#score comp 1 function
score_Comp1<- function(data){
  data$Comp1 <- rep(NA,nrow(data))
  data$Comp1 <- data$psqi_9_v2
  return(data$Comp1)
}
#Score comp 2 function
score_Comp2<- function(data){
  Score2 <- rep(NA,nrow(data))
  Score2[data$psqi_2_v2<=15] <- 0
  Score2[data$psqi_2_v2>15 & data$psqi_2_v2<=30] <- 1
  Score2[data$psqi_2_v2>30 & data$psqi_2_v2<=60] <- 2
  Score2[data$psqi_2_v2>60] <- 3


  Score_Comp2 <- Score2 + data$psqi_5a_v2


  data$Comp2[Score_Comp2==0] <- 0
  data$Comp2[Score_Comp2==1 | Score_Comp2==2] <- 1
  data$Comp2[Score_Comp2==3 | Score_Comp2==4] <- 2
  data$Comp2[Score_Comp2==5 | Score_Comp2==6] <- 3
  return(data$Comp2)
```

```
}
#score comp 3 function
score_Comp3<- function(data){
  data$Comp3[data$psqi_4_v2>=7] <- 0
  data$Comp3[data$psqi_4_v2>=6 & data$psqi_4_v2<7] <- 1
  data$Comp3[data$psqi_4_v2>=5 & data$psqi_4_v2<6] <- 2
  data$Comp3[data$psqi_4_v2<5] <- 3
  return(data$Comp3)
}
#score comp 4 function
score_Comp4<- function(data){
  risetime_hour = parse_date_time(paste("2022-07-19", datar$psqi_3_v2), order =
"%Y%m% d%H%M", tz = "America/Los_Angeles")
  bedtime_hour = parse_date_time(paste("2022-07-18", datar$psqi_1_v2), order = "%Y%m%
d%H%M", tz = "America/Los_Angeles")
  Hours_in_Bed<- as.numeric(risetime_hour - bedtime_hour)
  Hours_in_Bed[Hours_in_Bed>24] = NA
  #Hours_in_Bed[Hours_in_Bed>24] = hour(Hours_in_Bed-24)
  Score_Comp4 <- rep(NA,nrow(data))
  Score_Comp4 <- data$psqi_4_v2/Hours_in_Bed*100
  data$Comp4[Score_Comp4 >= 85] <- 0
  data$Comp4[Score_Comp4 >= 75 & Score_Comp4 < 85] <- 1
  data$Comp4[Score_Comp4 >= 65 & Score_Comp4 < 75] <- 2
  data$Comp4[Score_Comp4 < 65] <- 3
  return(data$Comp4)
}
#score comp 5 function
score_Comp5<- function(data){
  data$psqi_5othera_v2[is.na(data$psqi_5othera_v2) | data$psqi_5othera_v2==""] <- 1
  Score_Comp5 <- data$psqi_5b_v2 + data$psqi_5c_v2 + data$psqi_5d_v2 +
data$psqi_5e_v2 + data$psqi_5f_v2 + data$psqi_5g_v2 + data$psqi_5h_v2 +
data$psqi_5i_v2 + data$psqi_5othera_v2
  data$Comp5[Score_Comp5 == 0] <- 0
  data$Comp5[Score_Comp5 >= 1 & Score_Comp5 <= 9] <- 1
```

```
  data$Comp5[Score_Comp5 >= 10 & Score_Comp5 <= 18] <- 2
  data$Comp5[Score_Comp5 >= 19 & Score_Comp5 <= 27] <- 3
  return(data$Comp5)
}
#score comp 6 function
score_Comp6<- function(data){
  data$Comp6 <- data$psqi_6_v2
  return(data$Comp6)
}
#score comp 7 function
score_Comp7<- function(data){
  Score_Comp7 <- data$psqi_7_v2  + data$psqi_8_v2
  data$Comp7[Score_Comp7==0] <- 0
  data$Comp7[Score_Comp7==1 | Score_Comp7==2] <- 1
  data$Comp7[Score_Comp7==3 | Score_Comp7==4] <- 2
  data$Comp7[Score_Comp7==5 | Score_Comp7==6] <- 3
  return(data$Comp7)
}
```

PSQI Analysis

```
#PSQI Analysis and Import
#Author: Elena Austin/ McKay Reed
#July 17th 2022

setwd("/projects/austinlab/PSQI data")

library(pacman)
p_load(ggplot2, data.table, plyr, emmeans,psych)

data = fread("FirefighterRFStudy-ShiftNights_DATA_LABELS_2022-07-07_1201.csv")

data = data[`Complete?` == "Complete",]
```

```
#Number of surveys:

nrow(data)


#Responses by Department =

data.table(table(data$`Which fire district do you work for?`))


#Hours of sleep per night


ggplot(data, aes(`4. During the past month, while not on shift, how many hours of actual sleep did you get at night? (This may be different than the number of hours you spent in bed.)`)) +

  geom_histogram(binwidth = 1)  + theme_bw(12) + xlab("Hours of Sleep") + ylab("Number of Respondants") +

  ggtitle("PSQI Results", subtitle = "During the past month, while not on shift, how many hours of actual sleep did you get at night?")


ggplot(data, aes(`4. During the past month, while not on shift, how many hours of actual sleep did you get at night? (This may be different than the number of hours you spent in bed.)`)) +

  geom_histogram(binwidth = 1)  + theme_bw(12) + xlab("Hours of Sleep") + ylab("Number of Respondants") +

  ggtitle("PSQI Results", subtitle = "During the past month, while not on shift, how many hours of actual sleep did you get at night?")


#scoring the PSQI score


datar = fread("FirefighterRFStudy-CompleteQuestionaire_DATA_2022-07-19_1417_7_removed_military_corrected_pre_midnight_adjusted.csv")


datar$psqi_score = score_PSQI(datar)

#returning component scores

#component 1

datar$Comp1=score_Comp1(datar)

#component 2
```

```
datar$Comp2=score_Comp2(datar)
#component 3
datar$Comp3=score_Comp3(datar)
#component4
datar$Comp4=score_Comp4(datar)
#component 5
datar$Comp5=score_Comp5(datar)
#component 6
datar$Comp6=score_Comp6(datar)
#component 7
datar$Comp7=score_Comp7(datar)

ggplot(data = datar, aes(x = psqi_score)) + geom_histogram(binwidth = 1)
+xlab("PSQI Score")

#regression

ggplot(data = datar, aes(nights_on_shift, psqi_score)) + geom_point() +
  stat_smooth(method = "lm") +
  ggtitle("PSQI Score vs Nights on Shift")

datar[, nights_on_shift_bins := round_any(nights_on_shift, 3)]

ggplot(data = datar, aes(nights_on_shift_bins, psqi_score)) + geom_point() +
  stat_smooth(method = "lm") +
  ggtitle("PSQI Score vs Nights on Shift Rounded to Nearest Multiple of 3")+
  xlab("Night on Shift Rounded to Nearest multiple of 3")+
  ylab("PSQI Score")

reg1 = lm(psqi_score~nights_on_shift_bins, data = datar)
summary(reg1)
```

```
datar[psqi_4_v2<=6 , less_6_sleep := 1]

datar[psqi_4_v2>6 , less_6_sleep := 0]



reg2 = glm(less_6_sleep ~ psqi_score*nights_on_shift, data = datar, family =
"binomial")

summary(reg2)


reg2.emm.s  <- emmeans(reg2,~psqi_score*nights_on_shift, cov.reduce = function(x)
quantile(x, c(0, 0.25, 0.5, .75, 1)), type = "response")

reg2.emm.s

#create plot showing prob of less than 6 by nights on shift color=psqi score

#ggplot(reg2)

contrast(reg2.emm.s, by = "psqi_score")


contrast(reg2.emm.s, by = "nights_on_shift", type = "response", method = "poly")

#This has PSQI as independent, My interpretation is PSQI is the dependent

ggplot(datar, aes(psqi_score, nights_on_shift, color = less_6_sleep)) +
geom_point()


#Changing less 6 sleep to categorical

datar[psqi_4_v2<=6 , less_6_sleep_categorical := "6 Hours of Sleep or Less"]

datar[psqi_4_v2>6 , less_6_sleep_categorical := "More than 6 Hours of Sleep"]


#creating PSQI>5 variable

datar[psqi_score<=5 , Sleep_disturbance := "No signifigant sleep sleep
disturbance"]

datar[psqi_score>5, Sleep_disturbance := "Signifigant sleep sleep disturbance"]

#PSQI>5 numerical

datar[psqi_score<=5 , Sleep_disturbance_numerical := 0]

datar[psqi_score>5, Sleep_disturbance_numerical := 1]


#PSQI as dependent, categorical color key
```

```
#add trendline stat_smooth

ggplot(datar, aes( nights_on_shift_bins,psqi_score, color =
less_6_sleep_categorical)) + geom_point()+

  ggtitle("PSQI by Less than 6 Hours of Sleep and Nights on Shift ")+

  stat_smooth(method = "lm")+

  xlab("Nights on Shift Rounded to Nearest Multiple of 3")+

  ylab("PSQI Score")

reg3 = lm(psqi_score~nights_on_shift_bins*less_6_sleep, data = datar)

summary(reg3)


plot(reg3)

ggPredict(reg3,se=TRUE,interactive=TRUE)+

ggPredict(reg3.1,se=TRUE,interactive=FALSE)

reg3.1=lm(psqi_score~nights_on_shift_bins+less_6_sleep, data = datar)

summary(reg3.1)

plot(reg3.1)


AIC(reg3)

AIC(reg3.1)

BIC(reg3)

BIC(reg3.1)

anova(reg3,reg3.1)

plot

#ggplot(datar[!is.na(less_6_sleep),], aes(psqi_score, nights_on_shift)) +
geom_point() +

#  facet_wrap(~less_6_sleep) + stat_smooth(method = "lm")


#PSQI as dependent

#same info worse format than above plot

ggplot(datar[!is.na(less_6_sleep_categorical),], aes(nights_on_shift,psqi_score))
+ geom_point() +

  facet_wrap(~less_6_sleep_categorical) + stat_smooth(method = "lm")+

  ggtitle("PSQI vs Nights on shift by Hours of Sleep")
```

```
#PSQI as dependent nights on shift as dependent(round to nearest mult of 3)

#factor variable fire service

ggplot(datar[!is.na(fire_district),], aes(nights_on_shift,psqi_score,color=
less_6_sleep_categorical)) + geom_point() +

  facet_wrap(~fire_district) + stat_smooth(method = "lm")+

  ggtitle("PSQI vs Nights on Shift by Hours of Sleep and Fire District")



#PSQI>5 by district

ggplot(data=datar,aes(fire_district))+

  geom_bar(aes(fill=Sleep_disturbance, na.rm=TRUE))+

  ggtitle("Sleep Disturbance by District")

#sleep disturbance by nights on shift bins of 3

ggplot(data=datar,aes(nights_on_shift_bins))+

  geom_bar(aes(fill=Sleep_disturbance, na.rm=TRUE))+

  ggtitle("Sleep Disturbance by Nights on Shift Rounded to Nearest Mult of 3")

#regression nights on shift and less than 6 hrs of sleep as predictors of a sleep
disturbance

reg4 = glm(Sleep_disturbance_numerical ~ nights_on_shift*less_6_sleep, data =
datar, family = "binomial")

summary(reg4)

#component 1 boxplot by fire district

comp1p <- ggplot(datar, aes(factor(fire_district), Comp1))

comp1p + geom_boxplot(aes(fill = factor(fire_district))) +

  labs(title = "Subjective Sleep Quality by Fire District", x="Fire District",

                                                    y="Component 1 Score")+

  scale_fill_discrete(guide=FALSE)

#component 2 boxplot by fire district

comp2p <- ggplot(datar, aes(factor(fire_district), Comp2))

comp2p + geom_boxplot(aes(fill = factor(fire_district))) +

 labs(title = "Sleep Latency by Fire District", x="Fire District",
```

```
                                                 y="Component 2 Score")+
  scale_fill_discrete(guide=FALSE)
#component 3 hist by fire district
comp3p <- ggplot(datar, aes(factor(fire_district), Comp3))
comp3p + geom_boxplot(aes(fill = factor(fire_district))) +
 labs(title = "Sleep Duration by Fire District", x="Fire District",
                                                 y="Component 3 Score")+
  scale_fill_discrete(guide=FALSE)
#component 4 hist by fire district
comp4p <- ggplot(datar, aes(factor(fire_district), Comp4))
comp4p + geom_boxplot(aes(fill = factor(fire_district))) +
  labs(title = "Sleep Efficiency by Fire District", x="Fire District",
       y="Component 4 Score")+
  scale_fill_discrete(guide=FALSE)
#component 5 hist by fire district
comp5p <- ggplot(datar, aes(factor(fire_district), Comp5))
comp5p + geom_boxplot(aes(fill = factor(fire_district))) +
  labs(title = "Sleep Disturbance by Fire District", x="Fire District",
       y="Component 5 Score")+
  scale_fill_discrete(guide=FALSE)
#component 6 hist by fire district
comp6p <- ggplot(datar, aes(factor(fire_district), Comp6))
comp6p + geom_boxplot(aes(fill = factor(fire_district))) +
  labs(title = "Use of Sleep Medication by Fire District", x="Fire District",
       y="Component 6 Score")+
  scale_fill_discrete(guide=FALSE)
#component 7 hist by fire district
comp7p <- ggplot(datar, aes(factor(fire_district), Comp7))
comp7p + geom_boxplot(aes(fill = factor(fire_district))) +
  labs(title = "Daytime Disfunction by Fire District", x="Fire District",
       y="Component 7 Score")+
  scale_fill_discrete(guide=FALSE)
```

```
#component summaries by district

describeBy(datar$Comp1,datar$fire_district)

describeBy(datar$Comp2,datar$fire_district)

describeBy(datar$Comp3,datar$fire_district)

describeBy(datar$Comp4,datar$fire_district)

describeBy(datar$Comp5,datar$fire_district)

describeBy(datar$Comp6,datar$fire_district)

describeBy(datar$Comp7,datar$fire_district)

describeBy(datar$psqi_score,datar$fire_district)

#subsetting stations that were sampled for RF

Rf_Stations<-datar[datar$primary_station %in% c('12', '80', '74','75','76','46'),
]

#loading in rf data

data_RF=fread("Rf data for merging.csv")

#saving as integer data

data_RF <- data_RF %>%

  mutate(primary_station = as.integer(primary_station))

datar <- datar %>%

  mutate(primary_station = as.integer(primary_station))

#Merging rf and PSQI data

Data_RF_PSQI<-merge(data_RF,datar,by="primary_station")

#plotting  indoor Rf as a predictor of PSQI score

Data_RF_PSQI<-Data_RF_PSQI %>%

  mutate(Indoor_omnilog_ICNIRP_limit_percent =
as.numeric(Indoor_omnilog_ICNIRP_limit_percent))

ggplot(data = Data_RF_PSQI, aes(Indoor_omnilog_ICNIRP_limit_percent, psqi_score))
+ geom_point() +

  stat_smooth(method = "lm") +

  ggtitle("PSQI Score vs Indoor RF Measure")

#plotting outdoor omnilog rf vs psqi

ggplot(data = Data_RF_PSQI, aes(Outdoor_omnilog_ICNIRP_limit_percent,
psqi_score)) + geom_point() +

  stat_smooth(method = "lm") +
```

```
  ggtitle("PSQI Score vs Outdoor Omnilog RF Measure")

#plotting outdoor hyperlog rf vs psqi

#stat smooth not working

ggplot(data = Data_RF_PSQI, aes(Outdoor_hyperlog_ICNIRP_limit_percent,
psqi_score)) + geom_point() +

  stat_smooth(method = "lm") +

  ggtitle("PSQI Score vs Outdoor Hyperlog RF Measure")

#number of proximal cell towers as predictor of outdoor rf

ggplot(data = Data_RF_PSQI,
aes(number_of_proximal_cell_towers,Outdoor_omnilog_ICNIRP_limit_percent,

                                color=Urbanicity_Coding)) + geom_point() +

  stat_smooth(method = "lm") +

  ggtitle("Outdoor Omnilog RF vs Number of Proximal cell towers")


table(datar$Sleep_disturbance)

table(datar$less_6_sleep_categorical)

#comp1 by nights on shift

ggplot(data=datar,aes(nights_on_shift_bins,Comp1))+

  geom_point()+ stat_smooth(method="lm")+

  labs(title="Component 1 Scores by Nights on Shift Binned",

       x="Nights on Shift Binned to Nearest Multiple of 3",

       y="Component 1 Score")

#comp2 by nights on shift

ggplot(data=datar,aes(nights_on_shift_bins,Comp2))+

  geom_point()+ stat_smooth(method="lm")+

  labs(title="Component 2 Scores by Nights on Shift Binned",

       x="Nights on Shift Binned to Nearest Multiple of 3",

       y="Component 2 Score")

#comp3 by nights on shift

ggplot(data=datar,aes(nights_on_shift_bins,Comp3))+

  geom_point()+ stat_smooth(method="lm")+

  labs(title="Component 3 Scores by Nights on Shift Binned",

       x="Nights on Shift Binned to Nearest Multiple of 3",
```

```
       y="Component 3 Score")
#comp4 by nights on shift
ggplot(data=datar,aes(nights_on_shift_bins,Comp4))+
  geom_point()+ stat_smooth(method="lm")+
  labs(title="Component 4 Scores by Nights on Shift Binned",
       x="Nights on Shift Binned to Nearest Multiple of 3",
       y="Component 4 Score")
#comp5 by nights on shift
ggplot(data=datar,aes(nights_on_shift_bins,Comp5))+
  geom_point()+ stat_smooth(method="lm")+
  labs(title="Component 5 Scores by Nights on Shift Binned",
       x="Nights on Shift Binned to Nearest Multiple of 3",
       y="Component 5 Score")
#comp6 by nights on shift
ggplot(data=datar,aes(nights_on_shift_bins,Comp6))+
  geom_point()+ stat_smooth(method="lm")+
  labs(title="Component 6 Scores by Nights on Shift Binned",
       x="Nights on Shift Binned to Nearest Multiple of 3",
       y="Component 6 Score")
#comp7 by nights on shift
ggplot(data=datar,aes(nights_on_shift_bins,Comp7))+
  geom_point()+ stat_smooth(method="lm")+
  labs(title="Component 7 Scores by Nights on Shift Binned",
       x="Nights on Shift Binned to Nearest Multiple of 3",
       y="Component 7 Score")
#component vs binned nights on shift regressions
reg_comp1<- lm(Comp1~nights_on_shift_bins, data = datar)
summary(reg_comp1)
#compont 2
reg_comp2<- lm(Comp2~nights_on_shift_bins, data = datar)
summary(reg_comp2)
#component 3
```

```
reg_comp3<- lm(Comp3~nights_on_shift_bins, data = datar)
summary(reg_comp3)
#comp4
reg_comp4<- lm(Comp4~nights_on_shift_bins, data = datar)
summary(reg_comp4)
#comp5
reg_comp5<- lm(Comp5~nights_on_shift_bins, data = datar)
summary(reg_comp5)
#comp 6
reg_comp6<- lm(Comp6~nights_on_shift_bins, data = datar)
summary(reg_comp6)
#comp7
reg_comp7<- lm(Comp7~nights_on_shift_bins, data = datar)
summary(reg_comp7)
```

Nights on shift as a predictor of PSQI score regression summary

```
lm(formula = psqi_score ~ nights_on_shift_bins, data = datar)

Residuals:
    Min      1Q  Median      3Q     Max 
-6.1415 -2.9397 -0.7379  2.0603 10.0603 

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)    
(Intercept)            5.5451     1.0174   5.450 2.18e-07 ***
nights_on_shift_bins   0.2661     0.1120   2.376   0.0188 *  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.389 on 141 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.03851,   Adjusted R-squared:  0.03169 
F-statistic: 5.648 on 1 and 141 DF,  p-value: 0.01882
```

PSQI score and nights on shift as a predictor of getting less than 6 hours of sleep regression summary

```
Call:
glm(formula = less_6_sleep ~ psqi_score * nights_on_shift, family = "binomial",
    data = datar)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.1004  -0.5606  -0.2610   0.4380   2.6616

Coefficients:
                           Estimate Std. Error z value Pr(>|z|)
(Intercept)                -2.05196    2.32957  -0.881   0.3784
psqi_score                  0.28006    0.29822   0.939   0.3477
nights_on_shift            -0.52887    0.29489  -1.793   0.0729 .
psqi_score:nights_on_shift  0.05156    0.03616   1.426   0.1539
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 187.47  on 142  degrees of freedom
Residual deviance: 103.55  on 139  degrees of freedom
  (1 observation deleted due to missingness)
AIC: 111.55

Number of Fisher Scoring iterations: 6
```

Nights on shift and less 6 sleep as predictors of PSQI score model

```
Call:
lm(formula = psqi_score ~ nights_on_shift_bins * less_6_sleep,
    data = datar)

Residuals:
   Min     1Q Median     3Q    Max
-6.942 -1.381 -0.170  1.830  9.830

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                         4.9069     0.9255   5.302  4.4e-07 ***
nights_on_shift_bins                0.1404     0.1035   1.356   0.1774
less_6_sleep                        3.4521     1.5964   2.162   0.0323 *
nights_on_shift_bins:less_6_sleep   0.1467     0.1735   0.845   0.3994
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.507 on 139 degrees of freedom
  (1 observation deleted due to missingness)
Multiple R-squared:  0.4815,    Adjusted R-squared:  0.4703
F-statistic: 43.02 on 3 and 139 DF,  p-value: < 2.2e-16
```