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Spatial and Temporal Patterns of Fire on Saipan, CNMI[1]

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Abstract: Sediment core studies from Saipan suggest that fires did not play a prominent role in the disturbance regime of the Mariana Islands and have increased in frequency since human settlement around 4,000 years ago. On Saipan fires are understood to interrupt the pattern of succession leading to the degradation of native limestone forests, the proliferation of grasslands and the eventual creation of badlands. Little baseline data regarding the spatial and temporal patterns of fire on Saipan exist to create effective Fire Management Plans. This project uses Landsat 8 images from April 2013 to July 2020 and the Normalized Burn Ratio to identify historic fires to evaluate patterns that will inform on effective fire management policies. Over the study period we detected 1,608 ha of burnt land, in four specific hotspots. Of the area burned, 40% were in grasslands, 31% in evergreen forests, and 21% in scrub-shrub. 41% of all hectares that burned more than once throughout the study period were grasslands, indicating that this was the landcover type most vulnerable to repeat burn events. We also found a strong seasonal trend, with the average amount of burnt land detected in the dry season 280% higher than the average amount of burnt land detected in the wet season. Finally, both total precipitation and the absence of precipitation were highly correlated to the amount of burn area identified ($P < .05$). The information elucidated through this study will be used by local agencies to implement management plans geared toward controlling wildfires.

Keywords: Saipan, fire, ecology, LandSat, remote sensing

While wildfires are an extremely well-studied phenomenon in the continental United States, less is known about the ecological role they play on the Mariana Islands. Sediment cores taken from wetlands on the island of Saipan, Commonwealth of the Mariana Islands (CNMI), showed that charcoal was not found in identifiable quantities until approximately 4,000 years ago, coinciding with initial human settlement on the island (Athens and Ward 2004*a*). Further studies from Guam show similar patterns, with an absence of charcoal in the pollen record until about 4,200 years ago. Additionally, these studies suggest that grasses, a common disturbance indicator, did not become continuously present in the pollen record until 2,900 years ago (Athens and Ward 2004*b*). These grasses and other vegetation are known to exacerbate fire issues on other Pacific Islands by adding fuel to the system that would not have been present before human colonization (Trauernicht et al. 2015). With this information it is reasonable to assume that wildfires in the Mariana Archipelago did not play a prominent ecological role as they do in other ecosystems of the continental United States. As such, fires in their current state represent a human addition to the land that has led to drastic ecosystem

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changes, degrading native forests, a proliferation of non-native species, and expanding badlands—areas of exposed soil (Athens and Ward 2004*a*).

Fire is of particular importance to many Pacific Islands, including the CNMI, as it poses a direct and indirect threat to different ecosystems. On Saipan fires threaten native forests that are habitat and food reservoirs to Saipan's vulnerable and endangered species such as the ayuyu (*Birgus latro*), the totut (*Ptilinopus roseicapilla*), and the fanihi (*Pteropus mariannus*) (DCRM 2021). In the marine environment, as fires burn vegetation precipitation can erode the newly exposed soils down the slope gradient into streams and eventually the ocean. Once the soil enters the ocean it settles over corals reducing their ability to feed and photosynthesize, making them more vulnerable to bleaching (Minton 2006). Because of this dynamic, the National Oceanic and Atmospheric Association (NOAA) Coral Reef Conservation Program (CRCP) has a specific goal of reducing land-based sources of pollution by way of developing watershed management plans (NOAA CRCP 2018).

This broad understanding of fires is encoded in multiple of the CNMI's Bureau of Environmental and Coastal Quality (BECQ) Conservation Actions Plans (CAP, a precursor to the current Watershed Management Plans) that call for a reduction in the number of wildfires. Through outreach and management campaigns that aim to educate on safe fire practices, monitor fires, and facilitate conversion of grasslands back into forested areas, these CAPs aim to reduce the number of wildfires (BECQ 2009, BECQ 2013, BECQ 2015). This multifaceted approach to fire reduction addresses both the environmental and social conditions that facilitate fires on Saipan by removing the source of fires and the ability for wildfires to spread. However, many management plans acknowledge the knowledge gaps that exist relating to fires—stymieing their effective management. For instance, the State Wildland Fire Plan (SWFP) (Guerrero 2014) recognizes that Saipan is bereft of data related to historic fires that have occurred on the island. This data gap makes it difficult to study important questions such as what type of terrain is most impacted by fire, where fires occur most often, and how patterns of fire are changing over time. It is also noted that much of the information that is known about fires either comes from local knowledge that, while valuable, lacks quantitative backing, or from other islands that are only assumed to have similar fire dynamics. The CNMI is a region within the Pacific Fire Exchange (PFX), a network that seeks to "reduce [the] threat to ecosystems and communities in the Pacific from wildfire" (Trauernicht et al. 2018). To achieve this goal, the network helps create a space for knowledge exchange between islands. In 2014, a workshop of 14 PFX members convened to discuss knowledge gaps and rank them from low to high priority (Trauernicht et al. 2018). Using both these themes and the knowledge gaps listed in the SWFP as a guideline, we developed four questions related to wildfire management that will address concerns specific to Saipan:

1. What type of ecosystem is most vulnerable to wildfire?
2. Are locations vulnerable to repeat burning?
3. Have the number of hectares burned per year changed over time?
4. How do changes in precipitation correlate to larger amounts of fire?

Answering these four questions will aid in enacting established CAPs and contribute to the ability of Saipan to prepare for and mitigate future fires. Answering these questions will also support the calls for knowledge sharing and facilitate inter-island capacity building for fire management as seen in the PFX meetings. The information generated in this project will serve multiple different local CNMI agencies, including the Department of Land and Natural Resources (DLNR), Bureau of Environmental and Coastal Quality, and Department of Fire and Emergency Medical Services (DFEMS), as well as serve the greater Pacific Island conservation community that operates in similar fire prone ecosystems.

METHODS

This study took place on the island of Saipan, 15.19425°, 145.74716°. Saipan is both the largest in land area (11,538 ha) and has the largest population (48,000 permanent residents) of the twelve CNMI islands (CNMI Department of Commerce 2016). Saipan has a tropical environment with seasons being differentiated by precipitation instead of temperature. In the CNMI the wet season is comprised of the months July through December while the dry season is comprised of the months January through June (Lander 2004). Rainfall during the wet season averages 229 mm monthly and decreases to an average of 77.9 mm in the dry season. The temperature throughout the year remains relatively stable, averaging 33 °C. The island is highly mountainous with steep slopes running to the coast and large valleys created by perineal streams that egress into the ocean creating small estuary regions. The highest peak, Mount Tapochau, is located at the center of the island reaching an elevation of 474 m. This center area of higher elevation casts a rain shadow over the central and eastern part of the island. While actual precipitation data is limited to a few gauges located on the southern and central part of the island, remote sensing data show much higher cloud cover east of the Tapochau area indicating a higher level of precipitation on the east side of the island. Latest available Coastal Change Analysis Program (C-CAP) data shows that the land cover is comprised primarily of deciduous forests (62%), followed by developed open space (11%), impervious surfaces (i.e., roads, buildings, and parking lots–10%), and grasslands (6%) (NOAA 2016).

There are multiple different spectral indices (SI) identified in the literature that allow researchers to identify burn locations and assess burn severity. In this study the Normalized Burn Ratio (NBR) was utilized based on previous literature demonstrating its use in grasslands (Lu and He 2014, Meng et al. 2014, Xu et al. 2014) and its ability to identify both low and high severity burns (Key and Benson 2006). The index in particular is good at distinguishing between burned and unburned areas and is appropriate to use on 30-meter Landsat images allowing for landscape-scale analysis (Key and Benson 2006). Other methods used for fire detection in the CNMI, seen in the work by Dendy (2020) and the National Aeronautics and Space Administration's Fire Information for Resource Management Systems prove inadequate for this study due to the nonautomated nature of the methods, the low spatial resolution of the fire mapping, or the lack of freely available WorldView Imagery.

The NBR utilizes the difference in reflection of near infrared (NIR) and shortwave infrared (SWIR) to differentiate between healthy and burnt vegetation. Normalizing the ratio with the following equation $\frac{\mathrm{NIR}-\mathrm{SWIR}}{\mathrm{NIR}+\mathrm{SWIR}}$ places the index on a scale ranging from -1.0 to 1.0. NIR and SWIR wavelengths correspond to Landsat 8 bands 5 (0.85–0.88 μm) and 7 (2.09–2.35 μm), respectively, making the final equation for producing the NBR; $\frac{B5-B7}{B5+B7}$ (Key and Benson 2006). Typically, the difference between the pre- and post-fire NBR is used to isolate fires from background information creating the ΔNBR, however a lack of baseline data and the frequency of small-scale fires on Saipan makes the construction of and the interpreting of ΔNBR difficult.

C-CAP data was downloaded from NOAA's data catalog (NOAA 2016). This dataset shows the various landcover types of the CNMI and has a resolution of 30 m^2. Saipan was extracted from the overall dataset using a shoreline boundary shapefile generated by BECQ. Landsat 8 Thematic Mapper scenes, with a 30 m^2 resolution, were used to establish baseline fire data due to its open access and prior use in wildfire literature. The Landsat scenes were downloaded from the United States Geological Survey (USGS) housing website and stored locally. All images ranging from 2013 to present were checked manually via visual review to determine if they showed over 50% of Saipan unobstructed by cloud cover. Overall 60 images were included in the final analysis with an average of 7.5 images per year. The dry season months are more represented in the analysis with an average of five images per year, as compared to the wet season months with an average of 2.5 images per year. Once the image was downloaded, it went through five steps of processing within the geospatial software package ArcPro 2.4.0 (Esri Inc 2020). First, the index was calculated using the "Raster Calculation" tool. This produces an image wide NBR raster. The NBR of Saipan was then reclassified from a continuous −1.0 to 1.0 scale to a binary 0, 1 value with 0's representing pixels identified as not burnt, and 1's representing cells identified as burnt. Thresholding the NBR to separate burnt from unburnt locations proved difficult as short dry grass was a common false positive. Testing was performed on 14 May 2020 Landsat image that contains the only known location where short mowed grass caught on fire (Figure 1). A thresholding value of 0.1 proved the most successful at separating the burnt and unburnt grass at this location and was used for all 60 images.

To further reduce the false positives a mask consisting of impervious surfaces and water bodies was created from CNMI's 2016 C-CAP model and subtracted from the Saipan binary NBR. Next all images that were taken within 20 days were subtracted from each other to ensure a single burn did not receive a double-count between multiple images; this 20-day span being the observed minimum number of days for grasses to regrow to the point that they could carry another fire (Bubb, unpublished research, 2020). The number of cells classified as burnt were finally enumerated to estimate the total number of burnt hectares within the image. Finally, after an

FIGURE 1. Results of fire that burned at Coral Ocean Point on mowed golf course grass. This location was used for model threshold testing as it contains both short dry grass and burnt grass.

initial accuracy assessment of our NBR model we filtered out all isolated pixels that were identified as burnt to reduce false positives. This process was repeated for all 60 images in the analysis. Once all images were processed, they were stacked using the addition function of "Raster Calculation" tool to calculate how often each cell was classified as burnt within the temporal range of the study. While we can use this process to estimate the total number of hectares that burned within the study period, the total number of fires is difficult to estimate due to the temporal gaps between Landsat images and the high frequency of fires observed from the ground. For example, at Coral Ocean Point between the 28 April 2020 and the 14 May 2020 Landsat images, at least three separate fires were cataloged from field surveys, but since the fire boundaries were contiguous the latter Landsat image shows what looks like a single fire.

An accuracy assessment was conducted to evaluate our model's sensitivity, specificity, and kappa value. A total of 74 polygons representing fires identified from 2016 to 2019 had been digitized by partner researchers (Dendy 2020). This dataset was compared to our models to determine the ability of the models to produce true positives. Additionally, a Landsat image taken on 20 July 2020, was used to determine our model's ability to produce true negatives. This image was chosen as it was the latest image processed by USGS at the time of the study and contained a large range of small to large fires to test the model. The image release date was also within a week of the date that the image was taken meaning that any fires identified by the model would still be noticeable during ground truthing. A total of 35 random points within 30 m (the resolution of a Landsat-8 pixel) of the edge of a fire cell were selected in this image for field validation.

The effect of rain on fire was evaluated using Spearman non-parametric correlations between the total number of hectares burnt in a Landsat image and both the sum of all precipitation 132 days before the image and the number of days with less than 1 mm of rain 132 days before the image. 132 days was selected through an analysis that calculated the total precipitation and number of days with less than 1 mm of precipitation one day before each Landsat image up to 365 days before. The analysis found that the Rho value between total burnt hectares and total precipitation reached a maximum at 132 days before the Landsat image.

RESULTS

The results of this analysis indicate that fire is a common disturbance on Saipan. Over 1,608 ha of land has burned on the island since April 2013, with some detection of fire occurring in all but two of the 60 Landsat images. While the number of burnt hectares is much higher during the dry season, fire was detected in every month. Fires have been detected on Saipan ranging from the mountains to the coasts, only absent in the most urban or most densely forested areas. The largest concentration of fires occurs in four areas: Marpi, Wireless Ridge, Mt. Tapochau, and Naftan (Figure 2). Wireless Ridge and Mt. Tapochau contains the two largest grassland areas on Saipan and have had sections burn on four separate occasions during the study period. The grasslands within Naftan also repeatedly burn, with some parts burning on six separate occasions. The Marpi area has had the most repeated burns with pixels being identified as burnt 14 separate times. While Marpi and Naftan burn more regularly, the areas burned have a much smaller spatial extent burning on a scale of a tenth a hectare, compared to the Wireless Ridge and Mt. Tapochau fires that have footprints as large as 30 ha; although it is possible that these larger footprints were produced by multiple fires.

Overall, grasslands are the most common landcover type to burn, followed by evergreen forests and shrub cover types. During this study period, 630 ha of burnt grasslands were detected, compared to the 494 ha of evergreen forests. Most of the forests that burned were along the edges of grasslands that also burned. Very few evergreen forest or scrub dominated areas burned in isolation away from grasslands. Wetlands are the least burnt landcover type with only 2 ha burning throughout the study period. Grasslands, scrub-shrub,

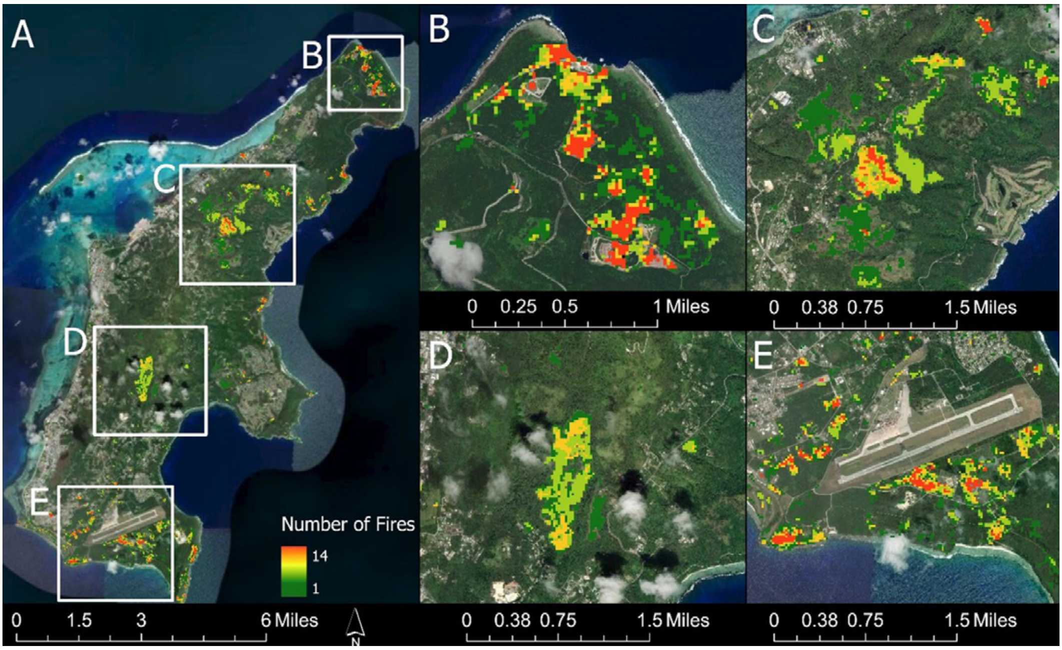

FIGURE 2. (*A*) All of Saipan with four different fire hotspots. (*B*) Marpi area. (*C*) Mt. Tapochau. (*D*) Wireless Ridge. (*E*) Naftan. In all images the redder a pixel is, the greater number of times that pixel was detected as burnt in the study.

cultivated land, and pastureland were landcover types that burned significantly more than expected under the null hypothesis that all landcover types are equally likely to burn. Conversely, evergreen forests and wetlands burned significantly less than expected (Table 1).

Repeat burns are common, with 26% of burnt hectares burning once and 74% burning two times or more (Figure 3). Breaking repeated burns down by landcover type, we found that the proportion of grasslands that burn more than once are significantly higher than the proportion that burn once. The opposite is true for forests, scrub-shrub, and wetlands, where we find that a significantly higher proportion of pixels burned once compared to more than once. The proportion of pixels that burned once compared to multiple times for other landcover types fell above the 0.5 *P*-value implying little to no significant difference (Table 2).

Two different precipitation metrics were compared to the number of identified burnt

TABLE 1

Number of Hectares Observed and Expected to Burn (Under the Null Hypothesis that All Landcover Types are Equally Likely to Burn) with Corresponding Chi-Square Goodness of Fit *P*-Value

	Observed	Expected	χ^2	DF	*P*-Value
Evergreen forests	45.90	90.59	18,887	1	<.0001
Grasslands	58.84	9.13	34,524	1	<.0001
Scrub-shrub	31.59	1.26	7044.3	1	<.0001
Cultivated land	3.70	1.02	412.92	1	<.0001
Pasture	5.92	0.03	144.19	1	<.0001
Wetlands (aggregated)	0.17	1.76	1122.8	1	<.0001

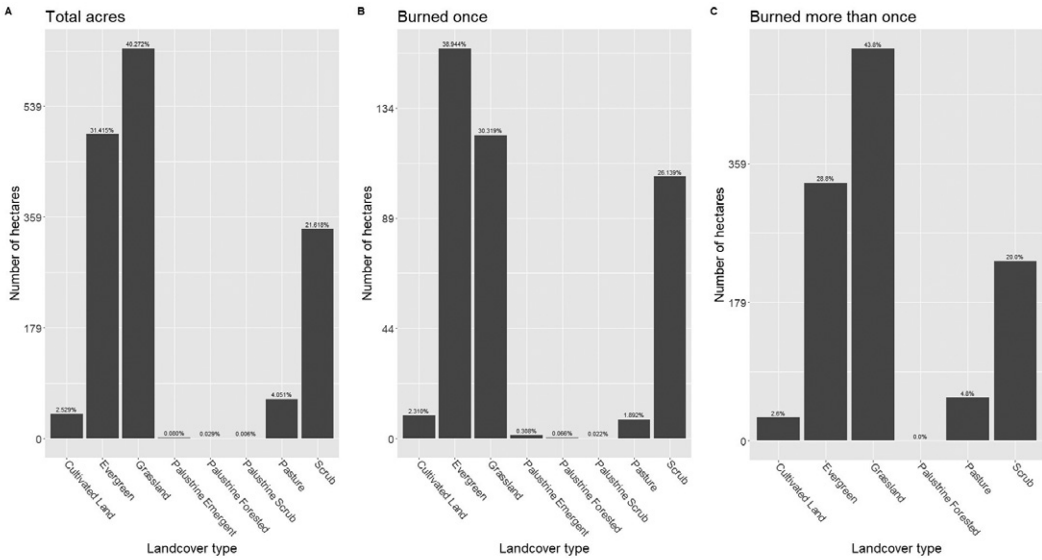

FIGURE 3. (*A*) The total number of hectares burnt separated by landcover type. (*B*) The total number of hectares that burned only once separated by landcover type. (*C*) The total number of hectares that burned more than once separated by landcover type. In all graphs, percentages show the proportion of each landcover type that burned out of the total number of hectares burned.

TABLE 2

Number of Hectares that Burned Once and More Than Once for Each Corresponding Landcover Type with Associated Two Proportion *Z*-Test Statistic, Degrees of Freedom, and *P*-Value

	Hectares Burned Once	Hectares Burned More than Once	X^2	DF	*P*-Value
Evergreen forests	159.3	334.8	161.15	1	<.0001
Grasslands	124.02	509.4	252.43	1	<.0001
Scrub-shrub	106.92	233.1.2	72.915	1	<.0001
Cultivated land	9.45	30.33	1.077	1	.299
Pasture	7.74	59.58	0.008	1	.927
Wetlands (aggregated)	1.8	0.18	45.044	1	<.0001

hectares in each image. We saw that as the cumulative amount of rain increases, the number of identified burned hectares decreases. Similarly, as the number of days with less than 1 mm of precipitation increases, so does the number of identified burned hectares (Figure 4). For both metrics a log transformation of the data was done and a paired Spearman's nonparametric correlation test was conducted ($P < .001$, $S = 55828$, $r_s = -0.71$; $P < .001$, $S = 10637$, $r_s = 0.69$). The Spearman's Rho values for each metric indicate a strong correlation between the two precipitation metrics and the number of burnt hectares detected (Akoglu 2018).

Analysis of temporal patterns reveals a strong seasonal influence on the amount of fire that occurs (Figure 5). An average of 34.1 ha of land was detected as burnt during the dry seasons, compared to an average of 12.1 ha detected as burnt during the wet seasons. Both images with zero detection of fire occurred in the wet season and the image with the highest amount of fire detection,

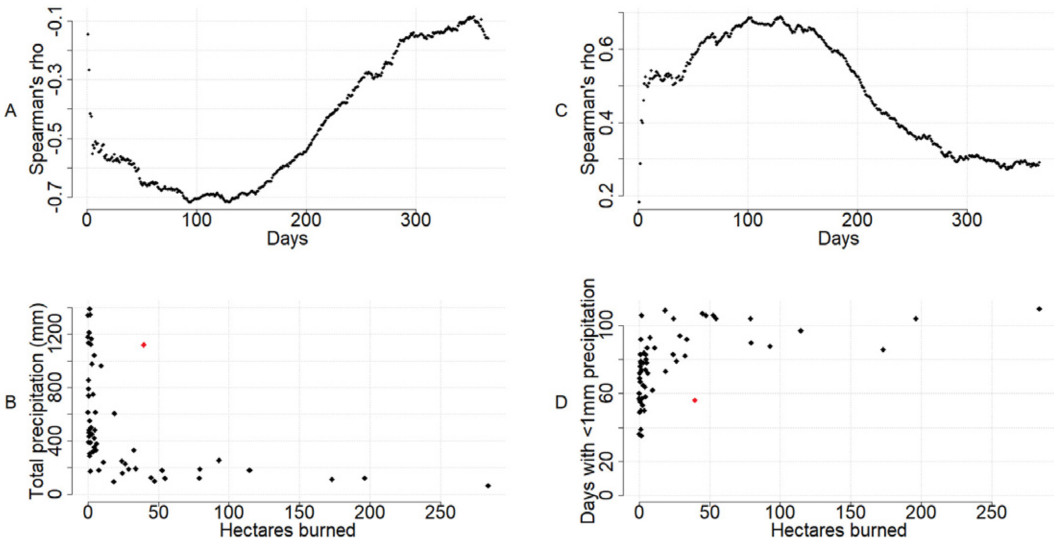

FIGURE 4. (*A*) The correlations between the summed total precipitation '*X*' number of days before a Landsat image and the number of burnt hectares detected. (*B*) The total precipitation 132 days before each of the 60 Landsat images and the number of hectares detected as burnt in each image. (*C*) The correlations between the summed total days with less than 1 mm of rain '*X*' number of days before a Landsat image and the number of burnt hectares detected. (*D*) The total number of days with less than 1 mm of precipitation occurring 132 days before each of the 60 Landsat images and the number of hectares detected as burnt in each image. The red point in graphs *B* and *D* represents the outlier in the data.

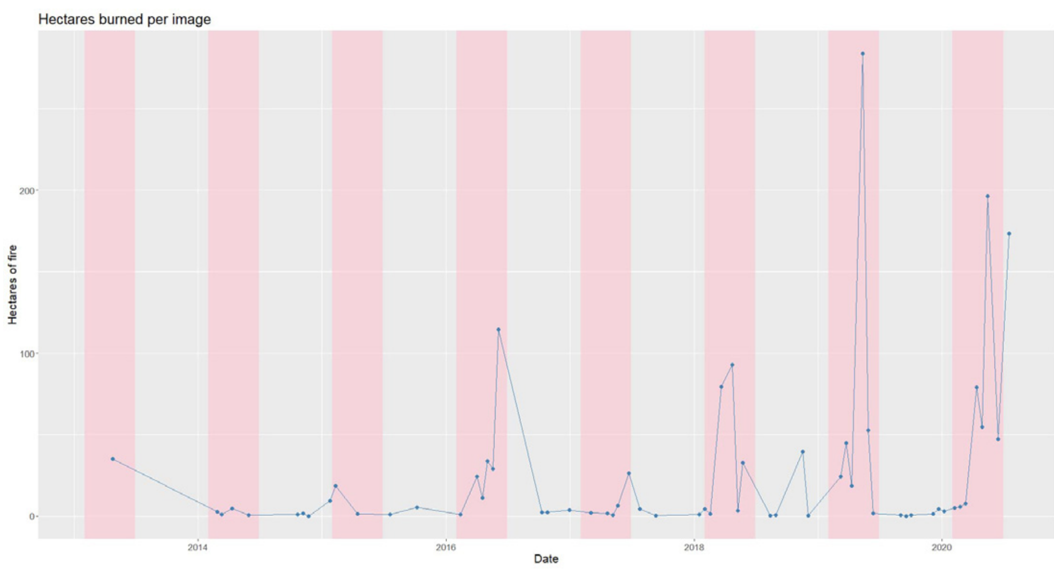

FIGURE 5. Number of hectares burnt throughout the study period. Points represent the number of hectares detected as burnt in each Landsat image. The pink bars show the dry season.

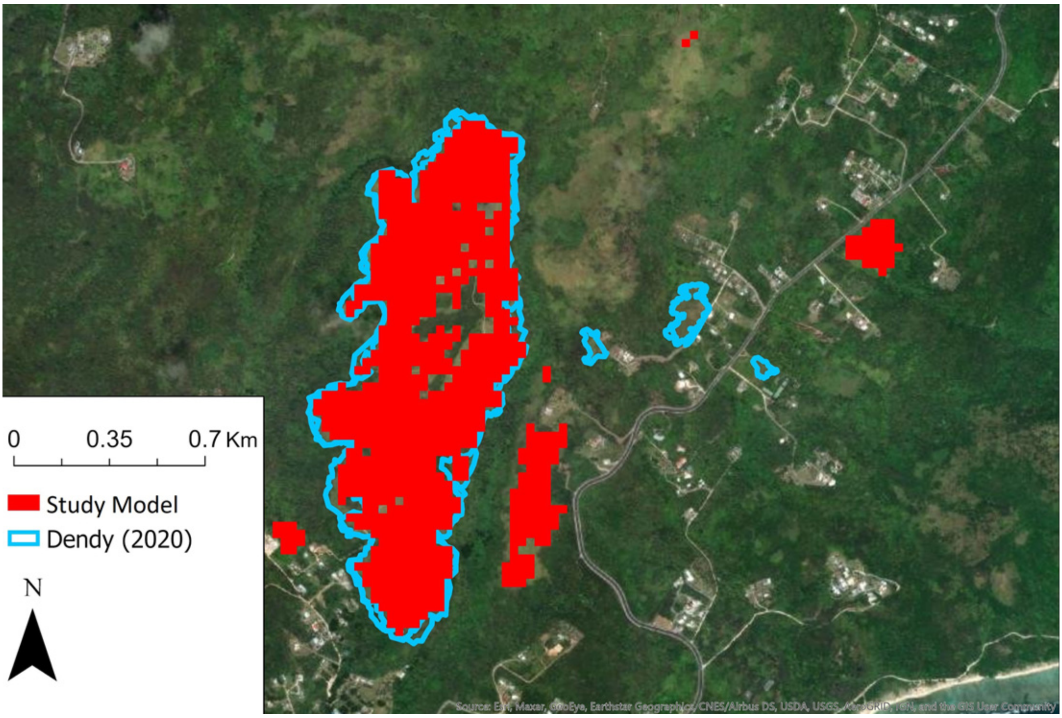

FIGURE 6. Fires occurring at Wireless Ridge throughout the study period. Red pixels show pixels detected as burnt in study model. Blue polygons represent fires manually digitized from Worldview Imagery, provided by Dendy (2020).

283.8 ha, was identified in the dry season. Overall, there is an increasing trend of fire detected over the duration of the study, with 2019 and 2020 having the largest amount of fire. These two years also had the least amount of rainfall during the dry season. The dry season in 2020 also had the largest contiguous burn event identified, at over 80.9 ha within the grasslands south of Mt. Tapochau, although it is possible that this was a result of multiple fires that coalesced between Landsat images.

An accuracy assessment was performed comparing 74 previously identified fires (Dendy 2020) to our model to evaluate true positives, and 35 randomly sampled points outside of fires that were reviewed in the field to determine rate of true negatives. Of these, 56 of the 74 previously identified fires were also detected by our model (Figure 6). After reviewing the 17 other fires it was determined that 10 were obscured by cloud cover in their corresponding Landsat image and the other seven occurred in Landsat images not included in the study due to high level of cloud cover. As such our model successfully detected 100% of the 56 previously identified fires that were possible to detect given the data used to create the model. Of the 35 points no-fire that were field verified, we found evidence of fire in seven of them. Overall, sensitivity was 0.891, specificity was 1.0, and our kappa value was 0.832 indicating strong model accuracy.

DISCUSSION

The results of this study provide important information for the future management of land and wildfire on Saipan. Specifically, several local management plans have called for a greater understanding of spatial patterns of fire in order to dedicate resources to areas with a higher vulnerability to fire. Four hotspots were identified as the most commonly burned locations on the island: Marpi, Wireless Ridge, Mt. Tapochau, and Naftan. Wireless Ridge and Mt. Tapochau represent the largest grassland areas on Saipan, and each burned multiple times within the study period. Fires in these areas are less frequent, but more expansive than in the Marpi and Naftan areas. The greater extent of fires in these regions probably occur due to the lack of forests, or large woody vegetation that would act as firebreaks. Furthermore, they are more isolated from urban centers, with few roads or houses that would hinder the spread of fires. As such, when a fire occurs in the Wireless Ridge or Mt. Tapochau grasslands it will spread without resistance until it finally reaches a forest edge, halting further burning. The Marpi and Naftan burn locations also occurred within grasslands, but these grasslands are more fragmented by roadways and other developed infrastructure. As such the fires in Marpi and Naftan have less space to expand until hitting a firebreak resulting in smaller fires. While the fires in these two areas are generally smaller, they burn more frequently, likely due to their proximity to a more urban environment which provides additional vectors for fire ignition.

Greene and Skeele (2014) discuss how climate change will likely impact the weather of the CNMI resulting in wetter wet seasons and drier dry seasons. Studies on Hawaii and Guam show that strong El Nino events produce similar results on Pacific islands and are also correlated to larger fire seasons. This is likely a result of wetter wet seasons increasing fuel loads of fire prone vegetation and drier dry seasons increasing the potential for a wildfire occurrence (Chu et al. 2002, Minton 2006). Data collected suggests that the total amount of rain and the number of days absent of rain preceding a fire event are both significantly correlated to the number of hectares burned. With climate change predicted to bring about fewer but heavier rain events while increasing drought conditions, precipitation patterns will trend towards conditions that facilitate larger and possibly more frequent wildfires (Greene and Skeele 2014). The trend might already be identifiable in the data with the last two dry seasons (2019–2020) accounting for 62% of the identified burn hectares. These years account for 21% of the study period but contain 23% of the days with 0 mm of recorded precipitation, and only 16% of the total rain recorded throughout the study period. Inversely the least amount of fire detected during a dry season occurred in 2014, which also coincides with an above average amount of precipitation (126 mm per month), emphasizing the role that rain has on controlling fires. One outlier in our study exists during the wet season where 39.6 ha of burnt land was detected on 17 November 2018, even though there was a cumulative 1,121 mm of rain in the 132 days before the image. This could possibly be explained by the fact that 23 of the 28 days directly before the image recorded zero precipitation resulting in an intense short-term dry spell.

This study provides a wide array of management implications. Differences between the Wireless Ridge/Mt. Tapochau fires and the Marpi/Naftan fires indicate that different location-based management strategies should be pursued in each area. In the urban Marpi and Naftan areas, in-person presentations and outreach lessons may be effective in reducing the number of chances for a fire to break out. Discussions with local fire emergency response teams have revealed that educational signage and posters along the few roads leading up to the Mt. Tapochau and Wireless Ridge may be a more effective management strategy than in-person measures as there is less overall access and people are more spread out. Revegetation is already outlined in the Achugao and Laolao Watershed Management Plans as a fire preventative, but this work suggests that revegetation efforts should focus along the fire breaks between grasslands in order to ensure that spread of fire is limited as much as possible. Revegetation projects in the Laolao watershed on Saipan and Talakhaya watershed on Rota, CNMI have already demonstrated their effectiveness at preventing fires (personal communications). Climate change will facilitate the drought conditions that support wildfires (Greene and Skeele 2014), and while management is unable to deal directly with changing precipitation patterns, revegetation and education can help prevent the human activities that start the initial fire. Revegetation projects such as green firebreaks have proven successful at reducing wildfires in other locations such as China, where over 364,000 km of green firebreaks have been planted, successfully reducing the intensity of fires at a cost-effective value (Cui et al. 2019). Over time revegetation projects should also derive ancillary benefits such as the revitalization of soil that have been eroded (Burri et al. 2009), reduce invasive species intrusion (Ellsworth et al. 2015), and reduce sedimentation stress on coral reefs (Wilkinson and Brodie 2011).

Emphasizing the importance of revegetation, we also found evidence that fires facilitate the expansion of grasslands and the contraction of native forests through burning. We saw that in grasslands with repeated burns, the successive burns would penetrate deeper into forest cover. This might indicate that forests are being converted into grasslands with each successive fire (Figure 7). Currently, Saipan's grassland areas are divided by barriers of forest and densely forested valleys that act as edges along grasslands. While fires rarely make the jump over these forest barriers, repeated fires can degrade the buffering vegetation and generate new connections between formally isolated grasslands, greatly increasing the risk for large-scale fires

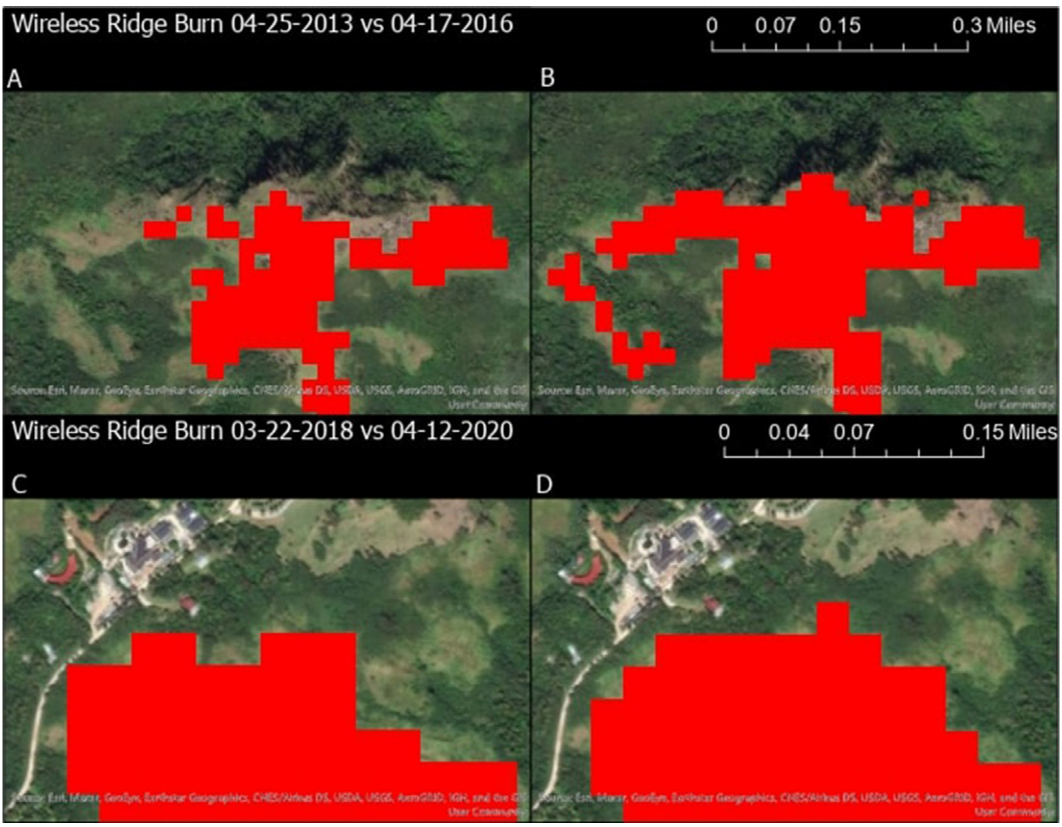

FIGURE 7. (*A*) Fire that burned on Wireless Ridge detected in 25 April 2013 Landsat image. (*B*) The same location that was detected as burnt again in 17 April 2016 Landsat image. (*C*) A Wireless Ridge fire that burned in 22 March 2018 Landsat image. (*D*) The same location that was detected as burnt again in 12 April 2020 Landsat image. Both *B* and *D* illustrate possible examples of how subsequent fires burn more expansively and possibly convert forest into grasslands.

to occur in the future. Repeated fires therefore have the potential to connect isolated grasslands, offering a greater risk to all individual areas in any given instance of fire. We also found that repeated burns were more likely to occur in grasslands and scrub-shrub than in forests. This is likely due to both the higher regeneration rates of vegetation in grasslands and the higher flammability of grasses compared to woody plants.

The process of forest conversion to grassland by fire is seen in other parts of the world. Armenteras et al. (2013) found that fragmented forests in the Amazon had a higher frequency of fires compared to unfragmented controls. Different processes such as wind and direct sunlight facilitate arid conditions, resulting in favorable fire conditions at these forest edges (Cochrane 2003). As such it has been shown in rainforests that a larger ratio of edge to total forest is associated with not only more fires, but faster deforestation (Cumming et al. 2012). Ibanez et al. (2012) demonstrate in New Caledonia that the shift from stable forested environment to savanna is primarily driven by anthropogenically caused fire, when controlling for grazing and logging pressure. They further show that shifts from savanna back to forest is most likely to occur in areas where savanna is surrounded by forested area offering greater chances of seed dispersal. Ibanez et al. (2013) investigate the forest edge relationship further showing that microclimates along the savanna–forest boundary help create conditions that prevent fire penetration into forest understory except in cases of extreme drought. They conclude that since fire suppression is unlikely, prescribed burns targeted during high moisture years could reduce fuel loads reducing forest burning when fires inevitably break out. Overall, these studies support our findings and suggest management strategies that include revegetation, drought monitoring, and the possible introduction of prescribed burning during wet seasons.

Data availability and cloud cover have been the most limiting factors to the study. Landsat 8 imagery only goes back to 2013 and while other Landsat data is available further in the past, they were not included due to the sensor differences between the two. Due to cloud cover, 17 fires that were known to have occurred between 2016 and 2019 were undetected by our models. This suggests that our model is an underestimate of the total amount of fires that occur on Saipan and that there is a probable bias towards fire detection during the dry season months due to the lower precipitation rates. While our model missed fires identified in previous research due to data gaps, it should be noted that our models were more accurate at omitting small patches of unburned forest within larger fires that were previously identified as having burned.

Our accuracy matrix showed that the method for fire detection was largely successful in distinguishing between burned and unburned vegetation. Our model was successful at identifying 100% of previously identified fires given the absence of cloud cover. False negatives occurred mostly around fires that were the size of the resolution of a Landsat 8 image. While our method of removing false positive and false negative pixels at this scale does not impact the overall trends found in the study, it does leave a knowledge gap in understanding the role that small-scale fires have on changing landscapes. This omission may be problematic as small-scale fires—such as residential trash burning, personal land, and farm clearing—undoubtedly play a role in starting larger fires. Furthermore, the removal of small-scale fires also increases the models false negative rate as multiple small-scale fires that were detected were removed from the final model.

This study opens questions for future investigation. First, the inclusion of Landsat 7 imagery would help increase the temporal span of the study and offer the ability to utilize the ΔNBR, allowing us to look at changes in fire intensity and spatial changes over a longer period of time. A pre- and post-fire landcover analysis is also needed to provide greater evidence for our theories on fire driven grassland expansion. While we have successfully elucidated broad fire patterns, finer scale analysis can lead to information on how fires spread along forest-grassland edges and the pace at which forests are then converted into grasslands. Additionally, little attention has been paid to differing role that invasive and native grasses have on spreading fires and how they differ in successive processes in a post-fire landscape. Lastly the baseline fire data created through this study can be used for future studies related to coral loss. Direct comparisons to water quality data that have been collected in the waters around Saipan may reveal connections between fires and water measures such as increased turbidity and total suspected solids—metrics that are known to impact coral health.

CONCLUSION

On small Pacific Islands fires have the potential to cause ecological problems for both the terrestrial and marine environment. On Saipan specifically, fires burn away vegetation and, in the process, exacerbate erosion, leading to the eventual sedimentation of coral reefs (DCRM 2021). Due to this, multiple management plans have outlined goals that serve to fill knowledge gaps related to weather conditions that facilitated fire, where and when fires occur, and how fires impact landcover. This study represents the first step at answering these questions by providing the first comprehensive fire baseline data for the CNMI. With this baseline data we estimate that 1,608 ha of land have burned between May 2013 and August 2020. We found that during this time fires were disproportionately found in grasslands, but were also found in scrub, pasture, and evergreen forest land cover types. We found that both increasing days without rain prior to Landsat image date and a lower volume of total amount of rain were significantly associated with increasing amounts of fire detection. With our analysis we were able to provide suggestions for future fire management: targeted revegetation of grasslands, outreach and education as methods to both prevent fires from occurring and mitigate against the damage of fires that manage to ignite. Finally, since our methodology is automated, utilizes freely available data, and has a relatively high spatial resolution, it represents an easily reproducible method of analyzing fires in other parts of the Pacific.

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Literature Cited

Akoglu, H. 2018. User's guide to correlation coefficients. Turk. J. Emerg. Med. 18(3): 91–93. https://doi.org/10.1016/j.tjem.2018.08.001.

Armenteras, D., T. M. González, and J. Retana. 2013. Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests. Biol. Conserv. 159:73–79. https://doi.org/10.1016/j.biocon.2012.10.026.

Athens, J. S., and J. V. Ward. 2004*a*. Holocene paleoenvironment of Saipan: Analysis of a core from Lake Susupe. Prepared for Division of Historic Preservation, Department of Community and Cultural Affairs, CNMI, Saipan, by International Archaeological Research Institute, Inc., Honolulu.

———. 2004*b*. Holocene vegetation, savanna origins and human settlement of Guam. Records of the Australian Museum, Supplement 29, 15–30.

Bureau of Environmental and Coastal Quality. 2009. Laolao Bay Conservation Action Plan. Bureau of Environmental and Coastal Quality, Saipan, CNMI.

———. 2013. Garapan Watershed Conservation Action Plan. Bureau of Environmental and Coastal Quality, Saipan, CNMI.

———. 2015. Sabana/Talakhaya Conservation Action Plan. Bureau of Environmental and Coastal Quality, Saipan, CNMI.

Burri, K., F. Graf, and A. Böll. 2009. Revegetation measures improve soil aggregate stability: a case study of a landslide area in Central Switzerland. Snow Landsc. Res. 82(1):45–60.

Chu, P., W. Yan, and F. Fujioka. 2002. Fire–climate relationships and long-lead seasonal wildfire prediction for Hawaii. Int. J. Wildland Fire 11:25–31.

CNMI Department of Commerce. 2016. HIES 2016 Population. Department of Commerce, Saipan, CNMI. https://ver1.cnmicommerce.com/hies-2016-population/.

Cochrane, M. A. 2003. Fire science for rainforests. Nature 421(6926):913–19. https://doi.org/10.1038/nature01437.

Cui, X., M. A. Alam, G. L. Perry, A. M. Paterson, S. V. Wyse, and T. J. Curran. 2019. Green firebreaks as a management tool for wildfires: lessons from China. J. Environ. Manage. 1:233:329–336. https://doi.org/10.1016/j.envman.2018.12.043. Epub 2018 December 22. PMID: 30584964.

Cumming, G. S., J. Southworth, X. J. Rondon, and M. Marsik. 2012. Spatial complexity in fragmenting Amazonian rainforests: do feedbacks from edge effects push forests towards an ecological threshold? Ecol. Complex. 11:67–74. https://doi.org/10.1016/j.ecocom.2012.03.002.

Dendy, J. 2020. Unpublished data. Support from Coral Reef Research Foundation, Palau and Institute of Pacific Islands Forestry, Hilo, HI.

Division of Coastal and Resource Management. 2021. Wildfire management. https://dcrm.gov.mp/our-programs/water-quality-and-watershed-management/wildfire-management/.

Ellsworth, L. M., C. M. Litton, and J. J. K. Leary. 2015. Restoration impacts on fuels and fire potential in a dryland tropical ecosystem dominated by the invasive grass *Megathyrsus maximus*. Restor. Ecol. 23(6): 955–963. https://doi.org/10.1111/rec.12263.

Esri Inc. 2020. ArcGIS Pro (Version 2.4.2). Esri Inc. https://www.esri.com/en-us/arcgis/products/arcgis-pro/.

Greene, R., and R. Skeele. 2014. Climate change vulnerability assessment for the Island of Saipan. Prepared for CNMI Office of the Governor – Division of Coastal Resources Management.

Guerrero, V. 2014. Commonwealth of the Northern Mariana Islands State Wildland Fire Plan. CNMI Forestry.rl H., and Nathan C. Benson. 2006. Landscape Assessment (LA) Sampling and Analysis Methods. USDA Forest Service - General Technical Report RMRS-GTR, no. 164 RMRS-GTR.

Ibanez, T., L. Borgniet, M. Mangeas, C. Gaucherel, H. Geraux, and C. Hely. 2012. Rainforest and savanna landscape dynamics in New Caledonia: towards a mosaic of stable rainforest and savanna states? Austral. Ecol. 38:33–45. https://doi.org/10.1111/j.1442-9993.2012.02369.x.

Ibanez, T., C. Hély, and C. Gaucherel. 2013. Sharp transitions in microclimatic conditions between savanna and forest in New Caledonia: insights into the vulnerability of forest edges to fire. Austral. Ecol. 38:680–687. https://doi.org/10.1111/aec.12015.

Key, C. H., and N. C. Benson. 2006. Landscape Assessment (LA) Sampling and Analysis Methods. USDA Forest Service – General Technical Report RMRS-GTR, no. 164 RMRS-GTR.

Lander, M. A. 2004. Rainfall climatology for Saipan: distribution, return-periods, El Niño, tropical cyclones and long term variations. Technical Report No. 103. University of Guam, Water and Environmental Research Institute of the Western Pacific. http://www.weriguam.org/docs/reports/103.pdf.

Lu, B., and Y. He. 2014. Analyzing a North American prairie wildfire using remote

sensing imagery. International Geoscience and Remote Sensing Symposium (IGARSS). 832–835. https://doi.org/10.1109/IGARSS.2014.6946553.
Meng, R., P. Dennison, C. D'Antonio, and M. Moritz. 2014. Remote sensing analysis of vegetation recovery following short-interval fires in southern California Shrublands. PloS One 9:e110637. https://doi.org/10.1371/journal.pone.0110637.
Minton, D. 2006. Fire, erosion, and sedimentation in the Asan-Piti watershed and War in the Pacific NHP, Guam. Pacific Cooperative Studies Unit, University of Hawaii at Manoa, Department of Botany, Honolulu (HI). PCSU Technical Report, 150.
National Oceanic and Atmospheric Administration, Coral Reef Conservation Program. 2018. Coral Reef Conservation Program Strategic Plan. NOAA, Silver Spring, MD.
National Oceanic and Atmospheric Administration, Office for Coastal Management, Commonwealth of the Northern Mariana Islands. 2016. Coastal Change Analysis Program (C-CAP) Regional Land Cover. NOAA Office for Coastal Management, Charleston, SC.
Trauernicht, C., E. Pickett, C. P. Giardina, C. M. Litton, S. Cordell, and A. Beavers. 2015. The contemporary scale and context of wildfire in Hawai'i. Pac. Sci. 69(4):427–444. https://doi.org/10.2984/69.4.1.
Trauernicht, C., E. Pickett, P. Beimler, C. P. Giardina, S. Cordell, J. B. Friday, E. Moller, and C. M. Litton. 2018. Assessing fire management needs in the Pacific Islands: a collaborative approach. Fire Manage. Today 76(1):30–35.
Wilkinson, C., and J. Brodie. 2011. Catchment Management and Coral Reef Conservation: a practical guide for coastal resource managers to reduce damage from catchment areas based on best practice case studies. Global Coral Reef Monitoring Network and Reef and Rainforest Research Centre Townsville, Australia, p. 120.
Xu, D., X. Guo, Z. Li, X. Yang, and H. Yin. 2014. Measuring the dead component of mixed grassland with Landsat Imagery. Remote Sens. Environ. 142:33–43. https://doi.org/10.1016/j.rse.2013.11.017.