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Article

Fire detection using subterranean soil sensors

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SUMMARY

Climate change and the resulting forest fires have devastated communities and caused ecological damage. Damaging fires are often detected very late, or firefighting resources are found lacking, leading to extensive damage. Existing fire detection methods, namely human-based observation, satellite systems, and optical cameras, have low-to-medium reliability. Wireless sensor networks (WSNs) are highly reliable but are plagued by false alarm repetitions. We aimed to engineer a fire detection system using soil-based sensors and mitigate the fire autonomously using harvested rainwater. We hypothesized that under a surface fire, soil temperature and moisture together should increase at a faster rate compared to when there is no surface fire, since under normal conditions, soil temperature should remain stable due to soil's high volumetric heat capacity. We also hypothesized that soil temperature at a shallow depth should increase faster than at deeper soil depths, since the heat gradient will decrease with depth. We built a WSN consisting of sensor nodes using temperature and moisture sensors deployed at multiple depths. The sensor nodes transmit data to the base station node (BSN) over radio waves. Field testing supported our hypotheses: Soil temperatures remained stable for long periods under normal conditions, but when a surface fire started, the soil temperatures and moisture rose rapidly. Also, the sensor deployed at one-inch depth saw a faster and higher rise in temperatures compared to the sensor deployed at three-inch depth. Therefore, we have developed a low-cost autonomous system that can detect, alert, and activate mitigative actions for communities during fire.

INTRODUCTION

Forest fires contribute 20% of carbon dioxide in the atmosphere and cause irreparable ecological damage (1). Due to increased urbanization of once-forested regions, more homes are at risk of wildfire damage (2). Climate change has increased the frequency of forest fires, devastating nearby communities (3). In these cases, the fires were either detected very late and had grown dramatically, or a lack of water and availability of firefighters hindered an adequate response (4). As multiple fires start in an area, fire response systems struggle due to the limited resources (4). Additionally, access and availability of water during a fire influence the containment costs (5). Helicopters ferry buckets of water to suppress wildfires, which is the most common technique but comes with a high hourly operating cost (5). Leveraging rainwater harvesting represents an exceptional opportunity for minimizing firefighting costs (5). Integrating a smart water pump (SWP) with a rainwater harvesting system can help lower these costs. However, to utilize this improved mitigation method effectively, there is a great need for a decentralized, low-cost, autonomous system that can detect, alert, and activate early mitigative actions. Such a system would provide time for self-evacuation and save lives.

Existing fire detection methods, namely human-based observation, satellite detection, optical cameras, and wireless sensor networks (WSNs), offer low-to-medium reliability (**Table 1**). Human-based observation methods cause detection delays (6). Satellite detection is costly and detects fires only after they have become large (6). Clouds and other environmental conditions impact optical camera-based solutions (6). WSNs are highly reliable but have issues that stem from the type of sensors used or the technology used for data or image capture (6). Smoke, gas, thermal, and flame detectors raise false alarms due to fog, clouds, sunlight, and non-smoke objects (6). Alternative solutions based on monitoring ambient surroundings must deal with air pollution issues and other environmental conditions, and these remotely installed systems also get destroyed or damaged in forest fires (7).

In this study, we aimed to use soil-based sensors for fire detection to overcome these limitations and develop a low-cost, highly reliable system that can survive surface fires. Given that the volumetric heat capacity of soil is very high, its temperature should remain stable under normal conditions and show an observable elevation under fire conditions. Researchers have previously found that a thermal gradient causes soil moisture to move from warmer to cooler soil (8). We hypothesized that the soil temperature and moisture should remain stable under normal conditions and rapidly rise under surface fire (**Figure 1**). Furthermore, we hypothesized that soil temperature at shallow depths should increase faster than at deeper depths (**Figure 1**). In all the tests that we conducted, we found that a dramatic rise in soil temperature occurred after a fire, and the soil temperature at one-inch depth rose faster than the soil temperature at three-inch depth. Our results consistently showed the moisture sensor at a one-inch depth rising rapidly before gradually decreasing. The moisture sensor at a three-inch depth also showed a slower rise before eventually decreasing. Therefore, we have developed a low-cost autonomous system that can detect, alert, and take mitigative actions for communities during fire using soil-based temperature and moisture sensors.

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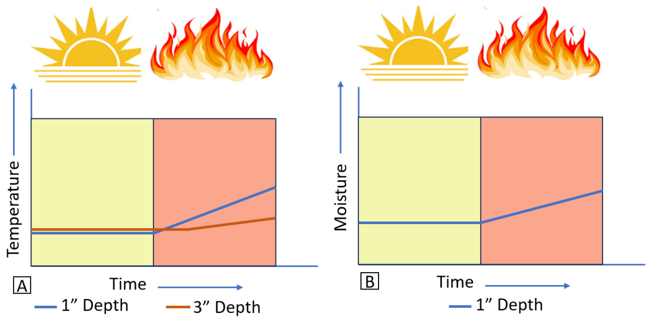

Figure 1: Expected soil temperature and moisture behavior before and after fire. We hypothesized that the **A)** soil temperature and **B)** moisture would remain stable under normal conditions and rapidly rise under surface fire. Furthermore, we hypothesized that soil temperature at shallow depths would increase faster than at deeper depths **(A).**

RESULTS

To test our hypotheses, we designed a WSN to measure soil temperature and moisture. The WSN consisted of a sensor node, a base station node (BSN), and a SWP (**Figure 2A**). The sensor node included two sets of soil temperature sensors, Sensor 1 and Sensor 2, installed under the soil at depths of one and three inches, respectively, and a single moisture sensor installed under the soil at a depth of one inch (**Figure 2B**). Sensor 2 provided insights into the time it took for heat to travel through soil and the temperature rise at different soil depths, helping us build an algorithm to detect the fire. We used only a single soil moisture sensor at one-inch depth to reduce the complexity of the fire detection algorithm.

We placed the BSN in a central location with access to Wi-Fi and dedicated power. The BSN tracked soil temperature and moisture data along with the running averages of temperature and moisture data for all the sensors. Under normal conditions, these running averages stabilized, and the readings showed flat-line behavior. Normal conditions were defined as when there was no surface fire, and any soil temperature change was able to be attributed to sun or weather-related changes. The running average of the latest five temperatures for both Sensor 1 and Sensor 2 were very similar (**Figure 3**).

Within four minutes of starting a controlled fire, Sensor 1's running average of the latest five temperature readings was 30% higher than its total running average. We defined this percentage, by which the average of the latest five readings is higher than the total running average, as the threshold. Within 11 to 17 minutes of starting a fire, Sensor 2's running average of the latest five temperature readings was 20% higher than its total running average (**Figure 4**). These findings supported the hypothesis that soil temperature will rise faster in a short period of time when there is a surface fire above the soil than when there is no fire. The hypothesis that the rate and magnitude of temperature rise will be higher at shallow soil depth than at deeper soil depth was also supported, as Sensor 1 saw a faster temperature rise rate than Sensor 2. Sensor 1 also reported a higher maximum temperature than Sensor 2 (**Figure 4A**). The moisture levels also rose during the surface fire (**Figure 5**).

We built this difference in the rate of rise in temperature and moisture for sensors at different depths into a fire detection algorithm hosted in the BSN (**Figure 6**). Our fire detection algorithm was designed to detect when a fire is occurring. The algorithm determines that a fire event is occurring when all the thresholds are surpassed: Sensor 1 is above 30%, Sensor 2 is above 20%, and the soil moisture sensor is above 10%. When the BSN detected fire, the BSN triggered the SWP to mitigate the fire using harvested rainwater (**Figure 2D**). We found that the BSN was able to call out the fire with a range of 14 to 20 minutes after the fire was started. To reduce the amount of time for the BSN to call out the fire, we decreased the threshold for Sensor 2 from 20% to 10%. We kept the threshold for Sensor 1 at 30%. As a result, the BSN reported a fire earlier, with a range of 10 to 11 minutes after the fire was started in various tests (n = 7).

Figure 2: Field testing setup. A) Sensor node, SWP and BSN components. **B)** The sensor node was installed under the soil with Sensor 1 and the moisture sensor placed at a one-inch depth and with Sensor 2 placed at a three-inch depth. **C) A** SWP was installed with **D)** a harvested rainwater barrel. **E)** On detecting rising soil temperature and moisture levels, the BSN triggered the SWP to extinguish the fire.

We conducted an additional test with two moisture sensors to understand how moisture behaves at different depths when there is a temperature gradient. We added a second moisture sensor to the sensor node at three-inch depth. We conducted multiple tests (n = 5), allowing the fire to burn for a few hours. The SWP was not used for these tests since the primary objective of this set of tests was to understand the impact on soil moisture under fire conditions. These tests consistently showed the moisture sensor at a one-inch depth rising rapidly before gradually decreasing. The moisture sensor at a three-inch depth showed a slower rise before eventually decreasing (**Figure 7**). We saw consistent results across tests conducted on different days with environmental temperatures ranging from 40°F to 84°F and environmental humidity ranging from 47% to 79%.

DISCUSSION

From the test results, we observed that under normal conditions, soil temperature and moisture below the ground change gradually. The only condition under which both the soil temperature and soil moisture rose rapidly was during a surface fire. We therefore reasoned that using soil temperature and moisture sensors could improve our ability to detect surface fires. Our methodology detects rapid changes in the last one minute and fifteen seconds compared to the

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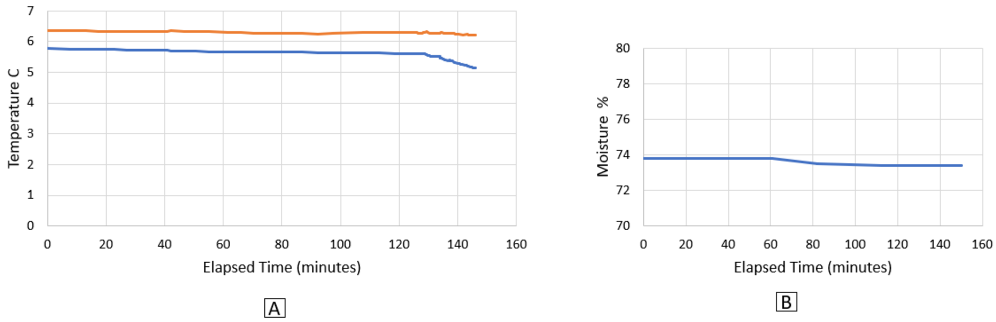

Figure 3: Representative soil temperature and moisture data during normal conditions. A) Soil temperature readings over time during normal conditions, when there was no fire, from Sensor 1 installed at a one-inch depth (blue) and Sensor 2 installed at a three-inch depth (orange). **B)** Moisture readings over time during normal conditions, when there was no fire, from the moisture sensor installed at one-inch depth. All sensors show flat-line behavior with Sensor 2 showing a slightly higher temperature than Sensor 1. These data are from a representative run (n = 7).

running average of the last four hours. Therefore, seasonal changes should not impact our methodology since it relies on detecting rapid variation in a short period. Our methodology also removes the need for any historical soil temperature and moisture data.

In all the tests that were conducted, we found a dramatic rise in soil temperature after a fire, and the soil temperature at Sensor 1 rose faster than the soil temperature at Sensor 2. We explain these results by the volumetric heat capacity of the soil. Since Sensor 2 had more soil cover, the sensor absorbed less heat energy, causing Sensor 2 to experience a more gradual rise in temperature. If we were to use both soil temperature sensors in tandem to detect a fire automatically, our results suggest that the Sensor 2 temperature rise threshold value should be set lower than the Sensor 1 temperature rise threshold value. The depth of installation of the sensors should determine the temperature rise threshold value to use, where a lower temperature rise threshold value is more appropriate if the sensor is installed deeper.

Using a higher temperature rise threshold value to detect fire automatically increased the probability of calling out the fire correctly but added to the delay in detecting the fire. Instead, the approach we used was a combination of two sensors at different depths with each sensor configured with an individual temperature rise threshold value. The highest soil temperature that we recorded during a fire event was 113°F before we called fire event. This temperature was well below the operating temperature range of the soil sensors ensuring the sensor node survived the fire in every experiment.

The behavior of the two-moisture sensor test was consistent with the established tendency of soil moisture to move from warmer to cooler soil under a temperature gradient (8). Based on these tests, we could enhance the fire detection algorithm in the future by adding a second moisture sensor at a three-inch depth. This will improve the reliability of the fire detection logic.

The sensor node successfully communicated using long range radio waves (LoRa) when buried under the soil with fire directly above it. However, we observed issues in processing radio wave transmissions. We sent messages using radio waves at a 915Mhz frequency, so the receiver could consume a message from any sender using radio waves at the same frequency. We saw this issue when the SWP tried to consume messages from the BSN but also consumed messages the sensor nodes sent to the BSN at the same frequency. This issue becomes more important when a WSN consists of a network of multiple sensor nodes and SWPs. We had to add logic so that the receiver would only consume messages from its expected sender and disregard messages from other senders.

We note that a soil sensor-based system only detects surface fires. Fire starting from a tree canopy will not be detected until the fire has reached the soil surface. The soil properties, such as thermal conductivity, thermal diffusivity, and volumetric heat capacity, inform the depth at which the sensor node should be deployed (9). The soil type and porosity must be accounted for to establish the installation depth (10). Hence, we would need to install sensors at a

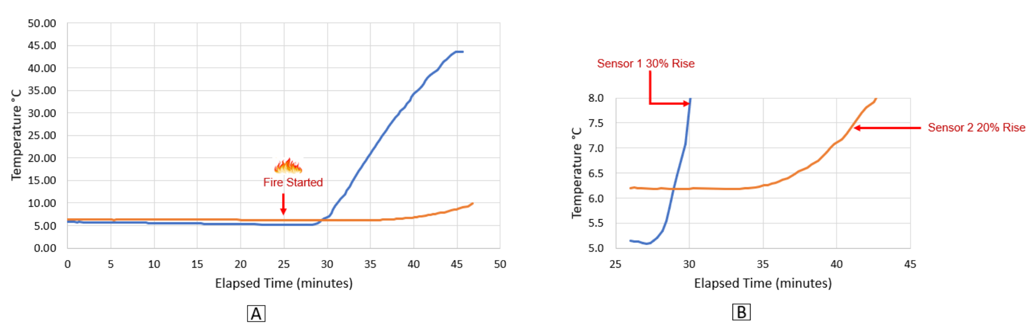

Figure 4: Representative soil temperature data during fire conditions. A) Soil temperature readings over time when a surface fire was started, from Sensor 1 installed at one-inch depth (blue) and Sensor 2 installed at a three-inch depth (orange). **B)** An expanded view of Sensor 1 (blue) and Sensor 2 (orange) between 25 and 45 minutes elapsed time. A dramatic rise in soil temperature was seen after starting a fire. The rate and magnitude of temperature rise was higher for Sensor 1 when compared to Sensor 2. These data are from a representative run (n = 7).

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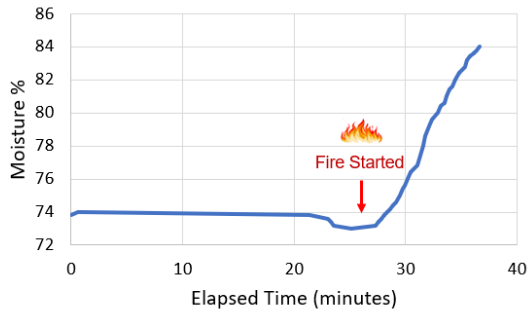

Figure 5: Representative soil moisture data during fire conditions. The soil moisture level at one-inch depth over time under surface fire conditions was seen to rise after a fire is started. These data are from a representative run (n = 7).

site-specific depth. We should conduct further experiments on different soil types with varying fire intensities, including testing the longevity of the sensors. Additional enhancements could include using wind speed and wind direction datasets to predict the fire's spread direction.

The system we developed can be used as a low-cost autonomous system that can detect, alert, and take mitigative actions for communities during fire without waiting on conventional firefighting resources. This system has the potential to be most useful around communities at high risk of forest fires and become their first response system. The system shows promise to be scaled up to provide relief when multiple fires in a jurisdiction overwhelm other available resources.

MATERIALS AND METHODS

Hardware configuration

The sensor node was comprised of two digital temperature sensors with adapter modules (Adafruit, DS18B20), a capacitive soil moisture sensor (DFRobot, SEN0193), a Nano board (Arduino, ATmega328P/CH340), LoRa wireless receiver transmitter (HopeRF, RFM95W 915Mhz), a rechargeable battery, and a solar panel (EverExceed, YXN-SP-L50). The capacitive soil moisture sensor measured the change in capacitance between two conductive plates in the soil as a function of soil moisture content. During each test, soil temperature was measured at a one-inch depth by Sensor 1 and at a three-inch depth by Sensor 2; soil moisture was measured at a one-inch depth. The BSN was comprised of a microcontroller (Arduino, Nano ESP32 IoT) and a LoRa wireless receiver transmitter (HopeRF, RFM95W 915Mhz). The SWP was built using a 12V DC freshwater pressure diaphragm pump (Bayite, BYT-7A102), a 5V one-channel relay module (AITRIP, 701715466746), a Nano board (Arduino, ATmega328P/CH340), LoRa wireless receiver transmitter (HopeRF, RFM95W 915Mhz), a 12V rechargeable battery, and a 12V 5W solar panel (EverExceed, YXN-SP-L50) to charge the 12V rechargeable battery.

Experimental procedure

The experiments were conducted across several days (30-Dec-2023 to 31-Aug-2024) at different field sites in Edison, New Jersey, between 12 pm to 6 pm ET. A controlled fire was started with charcoal briquettes in a separate chimney starter, and the charcoal briquettes were placed on the soil above the buried sensor node unit. All tests were done on grassy lawns with Boonton loam soil. The tests were repeated on days when the soil was dry and on days after rainfall.

Moisture sensor calibration

Capacitive soil moisture sensors were calibrated before the start of the study. The sensor readings for exposure to air and to water were used to set moisture readings of 0% dry soil and 100% wet soil, respectively. Specifically, the analog values for air and water measurements were 606 and 281, respectively. Analog values between 606 and 281 were mapped to soil moisture percentages using the map function from the Arduino math library, where 606 was treated as 0% and 281 as 100% moisture.

Data processing

The sensor node used the Dallas temperature software library (Arduino Library) to interface with the DS18B20 waterproof digital temperature sensor for retrieving soil temperature data. The sensor node took the soil temperature readings at one-inch (Sensor 1) and three-inch (Sensor 2) depths and moisture readings at one-inch depth. These three readings were transmitted in a single packet every 15 seconds over radio waves using the LoRa radio module. These transmission packets included a unique message identifier, the sensor node's own unique identifier, the unique identifier of the BSN, and the soil temperature and moisture data.

The BSN, on receiving these packets, checked the recipient identifier on the packet and only consumed the message if it was the BSN's unique identifier. The BSN also ensured that it did not consume a transmission packet with the same

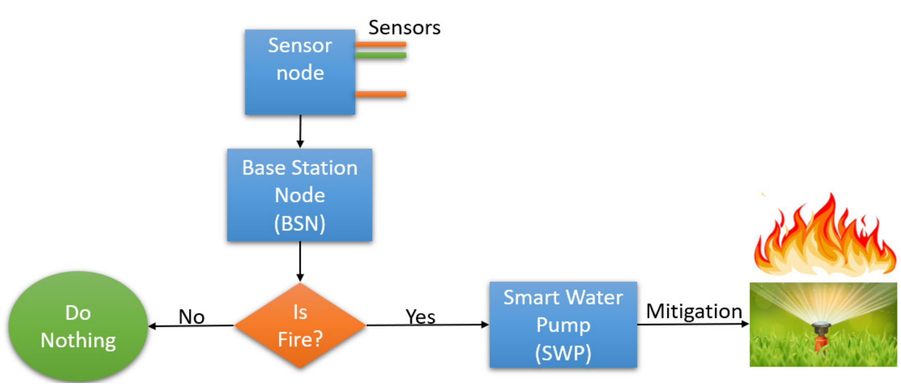

Figure 6: Logical schematic of the test setup. The sensor node, the BSN, and the SWP interaction during fire. The fire algorithm assesses data from the sensors to determine whether there is a fire. If fire is confirmed, mitigation actions are triggered.

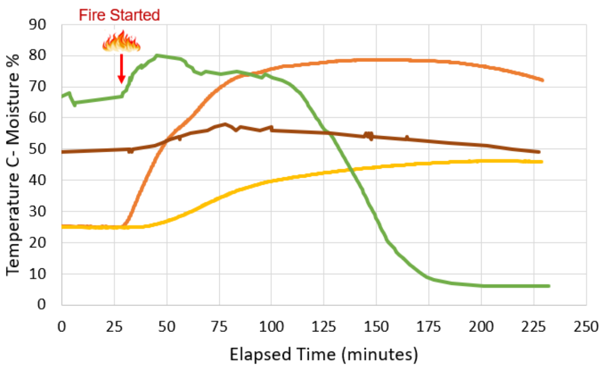

Figure 7: Representative soil temperature and moisture data under fire conditions and with no SWP mitigation. Soil temperature readings from Sensor 1 installed at a one-inch depth (orange) and Sensor 2 installed at a three-inch depth (yellow) and soil moisture readings from Moisture Sensor 1 installed at a one-inch depth (green) and Moisture Sensor 2 installed at a three-inch depth (brown) over time under fire conditions with no mitigation of the fire. Sensor 1 detected a rapid rise in temperature while Moisture Sensor 1 showed an increase before decreasing. Sensor 2 detected a gradual rise in temperature while Moisture Sensor 2 showed an increase before decreasing. These data are from a representative run (n = 5).

Message Identifier again. The BSN fire detection algorithm maintained a running average of the latest 1,000 readings (called TotalRunningAverage) and the running average of the latest 5 readings (called LatestRunningAverage) for the two soil temperature sensors and the single moisture sensor. Since the sensor node sent data every 15 seconds, the 1,000 readings provided TotalRunningAverage for 4 hours of data. The deviation of LatestRunningAverage from the TotalRunningAverage was defined as the threshold. Different thresholds were tested to determine the impact of the thresholds on the ability to reliably detect fire without adding delay in detection. When Sensor 1's LatestRunningAverage was higher than a threshold of 30% than its TotalRunningAverage, the BSN called a fire event for Sensor 1's reported data. The threshold for Sensor 2 was 10%. For the soil moisture sensor, the LatestRunningAverage and TotalRunningAverage of moisture were also maintained, and a threshold of 10% was used for calling out a fire event. When all these three threshold conditions were exceeded, the BSN called out the fire event. BSN uploaded all the data and any fire event to the IoT Arduino cloud.

The BSN filtered out any temperature and moisture readings that were outside of a certain range. Values less than half of the LatestRunningAverage were excluded. Values greater than double of the LatestRunningAverage were also excluded.

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