**Multi-Time Series Averaging of Ensemble Machine Learning Models Towards Crude Ol Price Forecasting**

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# Introduction

Crude oil and other refined liquid products from fossil fuels are critical contributors to the world economy. Petroleum has been the largest [energy source](https://www.eia.gov/energyexplained/us-energy-facts/) for all countries. Its products run vehicles, heat buildings, and produce electricity. Moreover, various industries use petroleum as a raw material to produce intermediate or end-user products that we use daily (EIA 2022b; Lu et al. 2021; Deng, Ma, and Zeng 2021; Kilian and Murphy 2014). In 2019, global petroleum consumption neared 100 million barrels per day (Table 1).

Table . The largest oil consumers and their share of total world consumption (EIA 2022b)

|  |  |  |  |
| --- | --- | --- | --- |
| Ranking | Country | Million barrels per day | Share of world total |
| 1 | United States | 20.54 | 20% |
| 2 | China | 14.01 | 14% |
| 3 | India | 4.92 | 5% |
| 4 | Japan | 3.74 | 4% |
| 5 | Russia | 3.70 | 4% |
| 6 | Saudi Arabia | 3.18 | 3% |
| 7 | Brazil | 3.14 | 3% |
| 8 | Canada | 2.63 | 3% |
| 9 | South Korea | 2.60 | 3% |
| 10 | Germany | 2.35 | 2% |
|  | World total | 100.23 |  |

### Problem statement

Crude oil prices are difficult to predict accurately due to the number of influencing factors and the highly complex behavior of such influences. Global economic and social activities can be substantially impacted by fluctuations in crude oil prices. Threfore, despite challenges for prediction of oil price, accurate oil price forecasting is crucial for decision-making support for the manufacturing, logistics, and government sectors to guide industrial and social policies and practices (Kilian and Murphy 2014; Deng, Ma, and Zeng 2021; Lu et al. 2021).

### Background

Brent, West Texas Intermediate (WTI), Dubai/Oman, and Shanghai crude oil prices are the major benchmarks of the crude oil market and are reported is USD per barrel unit. Factors such as supply and demand, financial markets and economics, politics, global events, renewable energy and alternative resources, new resources and development of new oil extraction technologies, social & environmental policies, and consumption patterns may influence the crude oil market dynamics. Such impacts and resultant price fluctuations might be very complex and may occur at different frequencies.

Classical econometric models such as random walk, autoregressive integrated moving average (ARIMA), error correction model (ECM), generalized autoregressive conditional heteroscedasticity (GARCH) model are used for crude oil price prediction. Recently, machine learning (ML) methods such as artificial neural network (ANN) and support vector machine (SVM) are used for the crude oil price prediction, which provide powerful tools to model nonlinear behavior or crude oil market dynamics (Jammazi and Aloui 2012; Lanza, Manera, and Giovannini 2005; Hou and Suardi 2012; Basiri 2015; Yu, Zhao, and Tang 2017; Murat and Tokat 2009; Kilian and Murphy 2014; Javadnejad 2012).

### Objectives

In this work, an ML model is proposed to predict crude oil price using multiple infulencing factors. The predictions are casted on multiple time-series to consider for complex factors that imact the market dynamics in differenct frequencies.

This report is structured as follows. Section 2.1 summarizes the datasets that are used in this study. Section 2.2 describes the data preparation and data wrangling procedures. In Section 2.3, the exploratory data analysis and feature engineering approcahes for ML training are described. Section 2.4 covers the ML pre-processing, training, models selection, model metrics. In Section 2.5, the final results for model training and validation are presented, as well as the predictions for 6-month time frequencies. We present the discussion of our results in Section 3. Finally, in Section 4, we summarise our recoomendaiton for future work.

# Methodology

We use PyCaret, an open-source low code Python library that automates machine learning (AutoML) models to construct and deploy the models (Moez 2022). The library manages twenty-five different algorithms for regression, such as Extra Trees Regressor (ET), Gradient Boosting Regressor (GBR), Extreme Gradient Boosting Regressor (XGB), Random Forest Regressor (RF), Linear Regression (LR), AdaBoost Regressor (ADA), and eighteen other algorithms for classification.

We compare the performance of twenty-five AutoML models based on coefficient of determination (R2), Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Then, we select the top five models for each time-series and build ensemble models. Ensemble methods benefit different training algorithms for increasing the training accuracy for reaching a higher testing accuracy to substantially improve the accuracy of the integerated model (Ardabili, Mosavi, and Várkonyi-Kóczy 2020).

Finally, the multi-frequnecy prediction time-series are weight-averaged based on the perfromance of the ML model into a single integrated predication series that represent the final oil price predictions.

## Datatets

The factors that influence the crude oil market dynamics include supply and demand, financial markets, politics, global events, alternative resources, development technologies, policies, and consumption patterns (Hamilton 2008; Hamilton 2009; Kilian and Murphy 2014; Zhao, Li, and Yu 2017; Lu et al. 2021; Wang, Wu, and Yang 2015). We use the crude oil prices of West Texas Intermediate (WTI) benchmark as the target feature. To take into account the aforementioned influencing factors a total of 32 feature variables were selected from publicly accessible data sources (EIA 2022a; FRED 2022; Investing 2022; WSJ 2022). Table 2 provides a list of the selected features, a description about each feature, and the sources of data.

Table . Selected dataset of feature variables for crude oil price

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Category | Symbol | Variable | Unit | Source |
| Crude Oil Price | WTIPUUS | West Texas Intermediate Crude Oil Price | dollars per barrel | EIA |
| Supply | COPR\_OPEC | Crude Oil Production, Total OPEC | million barrels per day | EIA |
|  | PAPR\_NONOPEC | Crude Oil Production, Total non-OPEC | million barrels per day | EIA |
|  | INTL.55-1-WORL-TBPD | Crude Oil Production, NGPL, and other liquids production, World | thousand barrels per day | EIA |
|  | COPRPUS | Crude Oil Production, U.S. | million barrels per day | EIA |
| Replacement Cost | RNGWHHD | Henry Hub Natural Gas Spot Price | dollars per million btu | EIA |
| Demand | PATC\_OECD | Liquid Fuels Consumption, Total OECD | million barrels per day | EIA |
|  | PATC\_NON\_OECD | Liquid Fuels Consumption, Total non-OECD, | million barrels per day | EIA |
|  | FEDFUNDS | Federal Funds Effective Rate | percent, not seasonally adjusted | FRED |
|  | IGREA | Index of Global Real Economic Activity | index, not seasonally adjusted | FRED |
|  | CICPIUS | US Consumer Price Index (CPI): All Commodities | index, 1982-1984=1.00 | EIA |
|  | USACPIENGMINMEI | US Consumer Price Index (CPI): Energy for the United States | index 2015=100, not seasonally adjusted | FRED |
|  | WPCPIUS | US Producer Price Index (PPI): All Commodities | index, 1982=1.00 | EIA |
|  | WP57IUS | US Producer Price Index (PPI): Petroleum | index, 1982=1.00 | EIA |
|  | EA19PIEAMI01GPM | roducer Price Index (PPI) of Euro Area (19 Countries) | index 2015=100, not seasonally adjusted | FRED |
|  | ZOMNIUS | US Manufacturing Production Index (PMI) | index, 2017=100 (seasonally adjusted) | EIA |
| Inventory | PASC\_OECD\_T3 | Petroleum Inventory, Total OECD | million barrels, end-of-period | EIA |
|  | PASXPUS | Petroleum Inventory, US Total | million barrels, end-of-period | EIA |
|  | COSQPUS | US Crude Oil Inventory: Strategic Petroleum Reserve (SPR) | million barrels, end-of-period | EIA |
|  | COSXPUS | US Crude Oil Inventory: Non-SPR | million barrels, end-of-period | EIA |
| Monetary Market | RTWEXBG | Real Broad Dollar Index | index Jan 2006=100, not seasonally adjusted | FRED |
|  | DXY | US Dollar Index (DXY) | index | Investing |
|  | DEXUSEU | U.S. Dollars to Euro Spot Exchange Rate (DEXUSEU) | US dollars to one euro, not seasonally adjusted | FRED |
| Stock Market | SPX | S&P 500 Index | index | WSJ |
|  | DJI | Dow Jones Industrial Index | index | WSJ |
|  | COMP | NASDAQ index | index | WSJ |
| Commodity Market | Gold\_Future | Gold Futures Historical Data | dollar per ounce | Investing |
|  | Copper\_Future | Copper Futures Historical Data | dollar per pound | Investing |
| Policy Uncertainty | GEPUCURRENT | Global Economic Policy Uncertainty Index: Current Price Adjusted GDP | index, not seasonally adjusted | FRED |
| Technology | MGWHUUS | Refiner Wholesale Gasoline Price | cents per gallon | EIA |
|  | DSWHUUS | Diesel Fuel Refiner Wholesale Price | cents per gallon | EIA |
|  | BREPUUS | Brent Crude Oil Spot Price | dollars per barrel | EIA |

## Data Cleaning and Data Wrangling

We used Jupyter Notebook 6.5.2 (Kluyver et al. 2016) and Python 3.9.15 (Python Software Foundation 2022) to process the data. The features in Table 2 were read through APIs (if available) or were downloaded directly from the data source. The data were initially set to be imported with monthly intervals or averaged to monthly values, then were limited to the target time frame of January 2000 and December 2022. The features were index based on their date values and then all merged together on the date values to create corresponding feature values for each month. Figure 1 shows the monthly West Texas Intermediate (WTI) crude oil price in the target time frame.

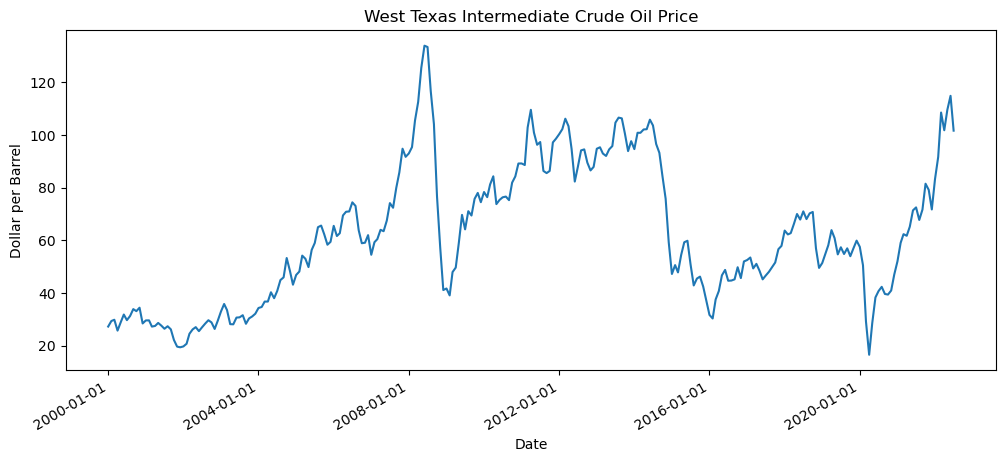


Figure . West Texas Intermediate (WTI) crude oil price

We used Pandas 1.5.2 (McKinney 2011) that is an open-source, simple, powerful, and flexible library for data analysis and data manipulation, Pandas is for Python programming language. The final dataset sized (274, 32) that represent 274-month records (rows) for 32 feature variables (columns).

An important step of data wrangling is dealing with missing data. Table 3 shows the summary statistics of missing data in feature variables. Missingno (Bilogur 2018) is also useful tool that provides a series of visualisations for presence and distribution of the missing data within a pandas dataframe. Figure 2 visually shows the distribution of the missing. To handle the missing data, features with more than the 10% of missing data were dropped from the dataset. The columns that had less than 1% missing features were imputed by using back and forward fill methods. For the remaining missing data between 1% and 10%, the rows for all features were dropped to create a dataset with no missing data. After treating missing data, the final dataframe sized (271, 30).

Table . Summary statistics of missing data in feature variables

|  |  |  |
| --- | --- | --- |
| Variable | Count | Percentage |
| oil\_production\_world | 3 | 1.1% |
| petroleum\_inventory\_oecd | 36 | 13.1% |
| global\_real\_econ\_activity\_index | 1 | 0.4% |
| us\_cpi\_energy | 1 | 0.4% |
| eu19\_ppi | 2 | 0.7% |
| real\_dollar\_index | 72 | 26.3% |
| global\_econ\_policy\_uncert\_index | 1 | 0.4% |

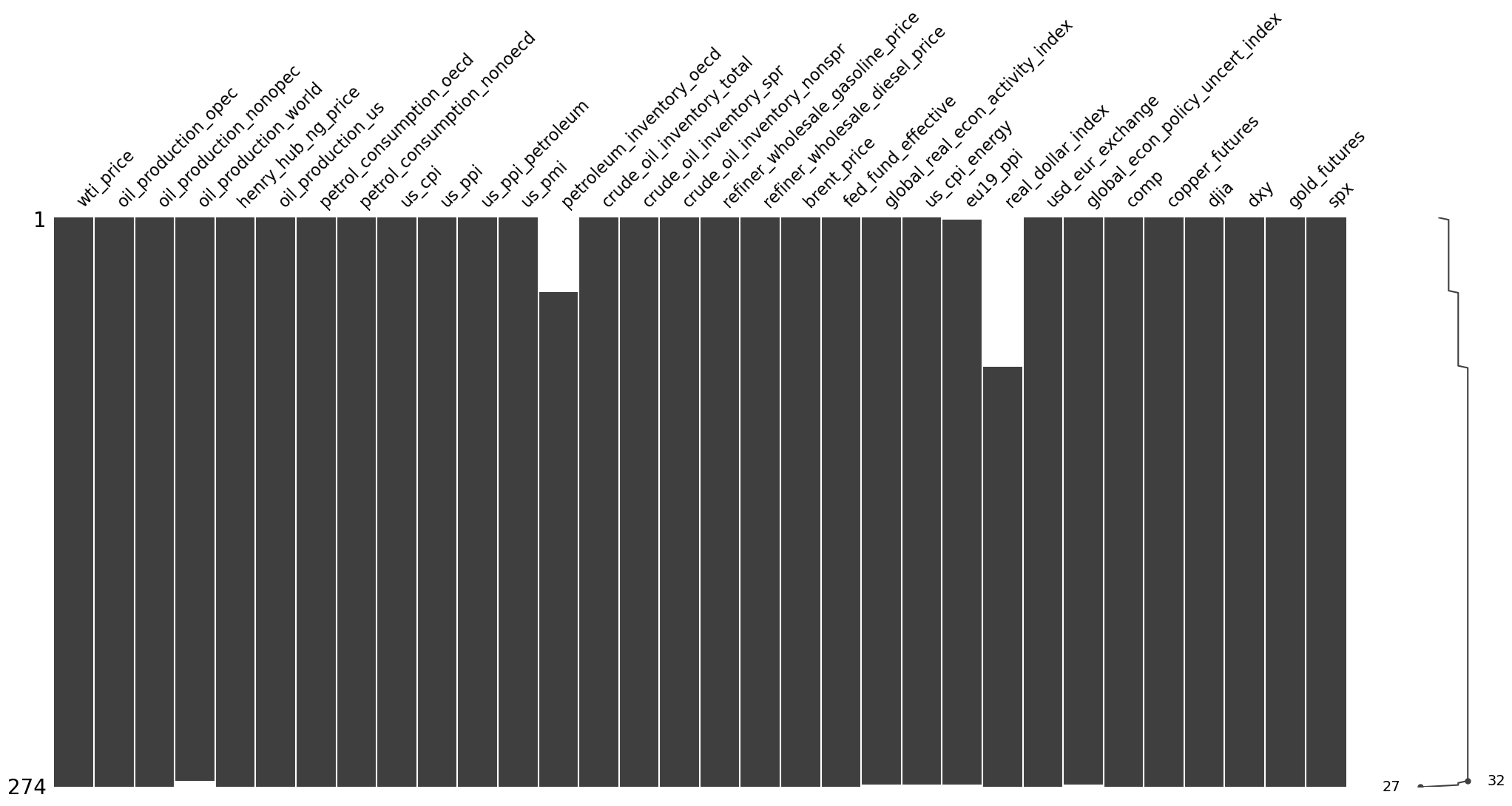
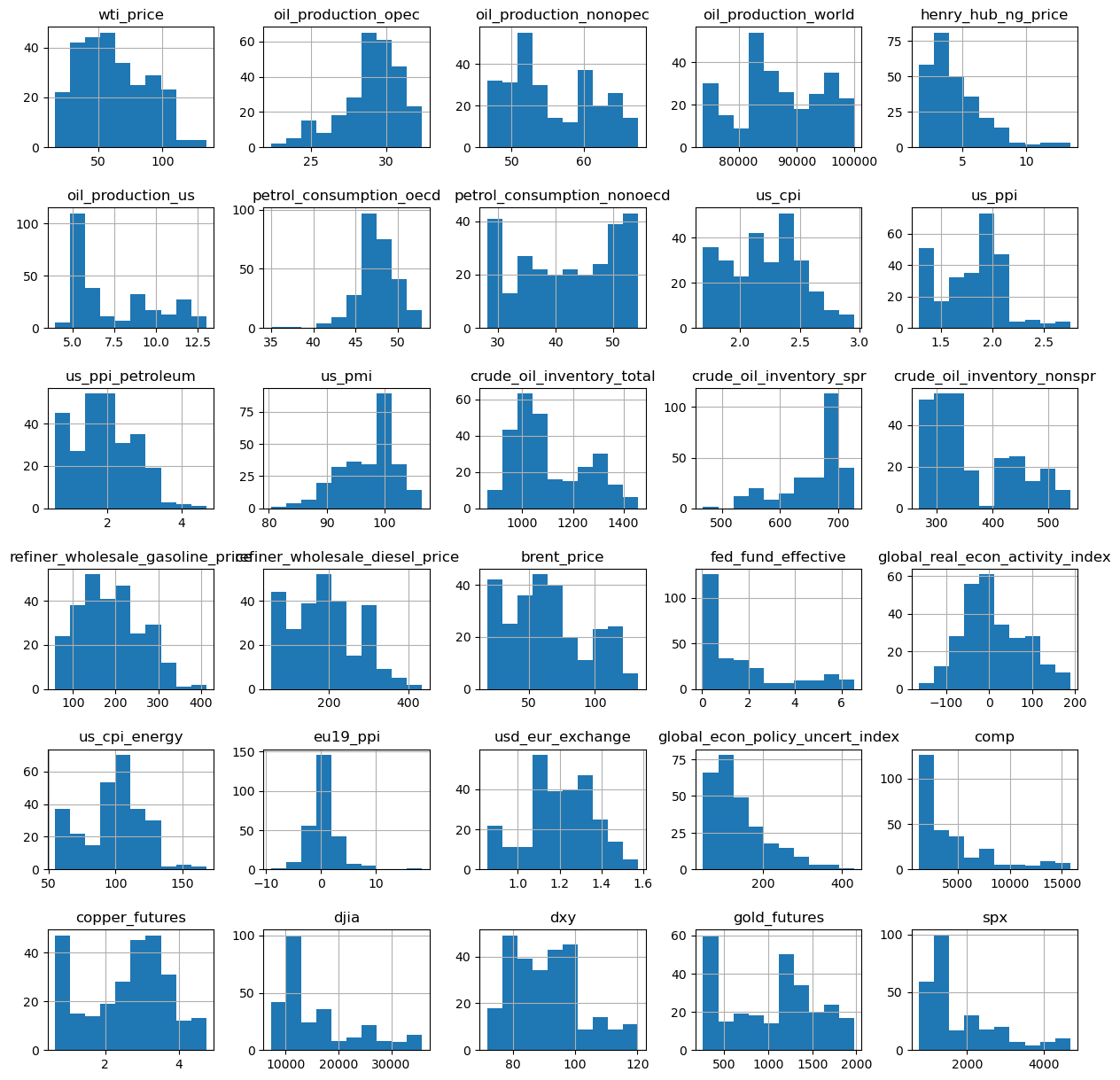


Figure . Missing data plot



## Exploratory Data Analysis and Feature Engineering

## Pre-processing and Training

## Modelling

# Results and Discussion

# Recommendations and Future Work

* Fused TIR and RGB 3D models generated from UAS imagery offer great potential for mapping heat loss, supplementing non-destructive testing of structures, aiding in the inspection of electrical parts, and more.
* This study tested a simplified approach for generating 3D TIR point clouds from coacquired TIR and RGB images for remote sensing applications. The constructed TIR point clouds are georeferenced to the same coordinate system as the RGB clouds. The resultant point cloud preserves the spatial density and resolution of the RGB point cloud while adding TIR attributes.
* The integrated visualization approach tested in this study enables 3D point cloud and 2D raster representation of RGB and TIR data in one model, enhancing the visual interpretation and analysis of the remotely-sensed data.
* The approach does not require additional depth sensors, such as lidar, or GNSS-aided INS for registration purposes.
* In general, the approach is appropriate for cases when….. For evaluation, and as examples of implementation…. While the SfM processing of RGB images was able to generate reliable….
* In future work, the proposed integration and visualization can be integrated into standard …... Radiometric calibration was considered beyond the scope of the present study; however, in-situ radiometric calibration of the thermal camera might improve the spectral content of the data. As an alternative …...
* TIR-RGB image feature matching and auto-registration can handle non-synchronized dual-head camera captures; however, extraction of identical features and co-registration based on the extracted pair is challenging for images of different spectral bands at the scene without well-designed calibration patterns.
* It is recommended that follow-on studies be conducted to address these topics…..

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