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Satellite-based assessment of the long-term efficacy of $PM_{2.5}$ pollution control policies across the Taiwan Strait

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ABSTRACT

Evaluating the efficacy of air pollution control policies is an essential part of the decision-making process to develop new policies and improve existing measures. Since 2005, Fujian Province of Mainland China and Taiwan across the Taiwan Strait have both implemented aggressive air pollution control policies designed based on different principles, but a comprehensive evaluation of these control policies on $PM_{2.5}$ pollution levels is still lacking. In the current study, we assessed the effects of these policies in the Taiwan Strait Region from 2005 to 2018 using full-coverage, high-resolution $PM_{2.5}$ generated by a satellite-driven machine learning model. A ten-fold cross-validation for our prediction model showed an R^2 value of 0.89, demonstrating that these predictions can be used for policy evaluation. During the 14-year period, $PM_{2.5}$ levels in all areas of Fujian and Taiwan underwent a significant decrease. Separate regression models for policy evaluation in Taiwan and Fujian showed that all considered policies have mitigated $PM_{2.5}$ pollution to various degrees. The Clean Air Action Plans (CAAP) is the most effective control policy in Taiwan, while the Action Plan of Air Pollution Prevention and Control (APPC-AP) and Three-year Action Plan for Blue Skies (3YAP-BS) as well as their provincial implementation plans are the most successful in Fujian. The effectiveness of control policies, however, varies by land-use types especially for Taiwan.

1. Introduction

Beyond visibility and ecosystem functioning, fine particulate matter (PM_{2.5}, particles with aerodynamic diameter smaller than 2.5 μ m) is also shown to pose threats to public health (Shaddick et al., 2018; Tutsak and Kocak, 2019; Wu et al., 2018; Xu et al., 2013). Globally, ambient PM_{2.5} has led to serious adverse health effects including cardiovascular and respiratory diseases and premature death (Chen et al., 2017; Hoek et al., 2013; Shah et al., 2013). In China, economic progress has come with increased occurrence of heavy PM_{2.5} pollution episodes in last decade, especially for the most developed regions (Deng et al., 2018; Xiao et al., 2017). The regions across the Taiwan Strait (TSR), covering Fujian of Mainland China and Taiwan, is flanked by two

highly polluted regions in China, i.e., the Yangtze River Delta (YRD) to the north and the Pearl River Delta (PRD) to the south. Endowed with a unique geographical location and abundant resources, the TSR is experiencing rapid urbanization and industrialization which have also given rise to accelerated emissions of PM_{2.5} from fossil fuel burning, urban sprawl and motor vehicles (Wu et al., 2018; Xu et al., 2013). PM_{2.5} pollution events have occurred frequently in the three metropolitan areas of Taiwan (Taipei, Taichung and Kaohsiung) due to booming economic growth, limited land and high population density (Zhou et al., 2019). In Fujian, due to increasing emissions as well as regional transport, its PM_{2.5} level has exceeded Chinese National Ambient Air Quality Standard I and differs between coastal cities and inland cities owing to the topography (Deng et al., 2014; Fu et al., 2018).

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Fig. 1. Spatial distribution of the ground monitors in the TSR. The background shows the elevation of the study domain.

To reduce the air pollution, a growing number of control policies were set for both Fujian and Taiwan in the past 15 years, but policies tailored to $PM_{2.5}$ pollution were only implemented in the last few years (Chen et al., 2019; Ma et al., 2019).

Evaluating policy effectiveness can verify successful measures and support the formulation of air pollution prevention and control policies in the future (Chen et al., 2019; Wang et al., 2018). Several emerging studies have evaluated historical control policies as well as their association with the trend of air pollution (Hu et al., 2010; Vennemo et al., 2009). Vennemo et al. (2009) proposed that China's progress in different regions in solving air pollution problems is lopsided, possibly due to the different policies implemented at local, regional and national scales. To analyze the effectiveness of different policies in typical Chinese cities, Hu et al. (2010) studied the air pollution problems, air pollution control measures and the effects of these measures for each city, concluding that local governments should develop stricter control measures suited to their regions. Jin et al. (2016) studied the development of China's air pollution prevention and control policies since the 1980s, drawing the conclusion that China's policies at emission reduction before 2005 were ineffective. This study also indicated an increasingly regional air pollution problem dominated by PM_{2.5} and ground ozone (O₃) during the implementation of the 11th Five-Year Plan (2006-2010) as well as significant changes in control policies in eastern China after the year 2013. Ma et al. (2019) used satellite PM_{2.5} data from 2005 to 2017 to evaluate Mainland China's control policies, proving that these policies have led to a big drop in PM_{2.5} since the implementation of the toughest-ever clean air policy in China after 2013. This finding was further confirmed by Zhang et al. (2019). However, assessments of the long-term efficacy of air pollution policies on PM_{2.5} are limited (Buckley and Mitchell, 2010; Carnevale et al., 2008; Gao et al., 2016; Li et al., 2019; Vlachokostas et al., 2009). Even fewer comparisons exist on the effectiveness of control policies guided by different theories and implemented in different political system.

Owing to similar meteorological conditions and close geographic position, Fujian and Taiwan are reported to experience comparable $PM_{2.5}$ transportation from emission hotspots in East China (Deng et al., 2014). However, being a part of Mainland China, Fujian implements both national and regional air pollution policies, with regional policies

usually extending those of the national level. On the other hand, Taiwan has set the same $PM_{2.5}$ concentration standard as United States (Yang et al., 2017a), and designed its control policies mostly following the examples of developed countries in North America and Europe. Over the past 15 years, the $PM_{2.5}$ characteristics and trends have been affected by the control policies implemented in these two regions. Hence the TSA presents a unique opportunity to compare the efficacy of policies designed under two distinct conceptual frameworks.

An accurate spatiotemporal PM2.5 dataset is the foundation for evaluating the performance of air pollution policies (Geng et al., 2017; Ma et al., 2016). Current studies mainly rely on chemical transport models (CTMs) and remote sensing techniques to predict the PM_{2.5} concentration. The uncertainties of CTM-simulated PM2.5 are often high and vary in space (Geng et al., 2017). CTMs must consider existing policies and their designed impacts in the development of their emissions inventory. As a result, their simulation results are not proper to evaluate the actual impact of these policies. Data-driven models using statistical and machine learning approaches were applied in TSR and the adjacent region in recent years (Chu and Bilal, 2019; Jung et al., 2018; Wu et al., 2018; Yang et al., 2017, 2019). For example, Chu and Bilal (2019) and Jung et al. (2018) mapped the PM_{2.5} concentration of Taiwan respectively based on geographically temporally weighted regression with random sample consensus modeling ($R^2 = 0.83$) and a linear mixed effects (LME) model ($R^2 = 0.66-0.77$). Recent machine learning algorithms such as the artificial neural networks (Di et al., 2016) and random forests (RF) (Huang et al., 2018) using high-resolution satellite-derived aerosol optical depth (AOD) datasets generated from the Terra and Aqua instruments like the Multi-Angle Implementation of Atmospheric Correction (MAIAC) AOD for PM2.5 prediction have reported good model performance with high R² values.

The objective of this study is to evaluate the effects of air pollution control policies on $PM_{2.5}$ concentration in the TSR from 2005 to 2018. Based on long-term and high-resolution monthly $PM_{2.5}$ concentration provided by our $PM_{2.5}$ prediction model, evaluation of the major control policies implemented in TSR will be conducted. Finally, the most effective policies in Taiwan and Fujian during the 14-year period will be identified and the effectiveness of control strategies on the $PM_{2.5}$ concentration by land-use types will be assessed.

Table 1

Major air pollution control policies of Fujian and Taiwan from 2005 to 2018.

Regions	Policies	Implementation period
Fujian Taiwan	 11th Five-year Plan on Environmental Protection and simultaneous Energy Conservation and Emissions Reduction; 11th Fujian Five-year Plan on Environmental Protection and simultaneous Fujian Energy Conservation and Emissions Reduction 12th Five-year Plan on Environmental Protection and simultaneous Energy Conservation and Emissions Reduction; 12th Fujian Five-year Plan on Environmental Protection and simultaneous Fujian Energy Conservation and Emissions Reduction; 12th Fujian Five-year Plan on Environmental Protection and simultaneous Fujian Energy Conservation and Emissions Reduction; Air Pollution Prevention and Control in Key Regions 	2006–2010; Actual start at 2007 2011–2015; Actual start at 2012 2011–2015; Actual start at 2012
	 Action Plan of Air Pollution Prevention and Control; Fujian Action Plan of Air Pollution Prevention and Control Amendments to the Law of the People's Republic of China on the Prevention and Control of Atmospherics Pollution Three-year Action Plan aims for Blue Skies; Fujian implementation plan of Three-year Action Plan aims for Blue Skies 7th amendments to the Air Pollution Control Act; 	1. 2013–2017; 2. 2014–2017 2016–2018 2018–2020 2011–2018
	 Amendments to standards for the sulfur content of diesel fuels 8th amendments to the Air Pollution Control Act; Amendments to standards for the sulfur content of automobile gasoline; 5th emission standard of diesel and gasoline vehicles Innovative PM_{2.5} Control Strategies Clean Air Action Plans; Amendments to Clean Air Action Plans I Air Pollution Control Strategy Air Pollution Control Strategy Air Pollution Control Action Plan; 9th Amendments of Air Pollution Control Act 	2012–2018 2014 1. 2015–2016; 2. 2016–2019 2017–2019 1. 2018–2040; 2. 2018-

2. Data and methods

2.1. Study area

Lying in the southeast of China, Fujian and Taiwan are both areas with mountainous landscapes (Fig. 1.). The populations of Fujian and Taiwan are 38.39 million and 23.49 million, respectively (Fu et al., 2018; Wu et al., 2018). Southwest Taiwan was the most polluted area, in particular Kaohsiung City and its neighborhood. Previous studies found that the major source of $PM_{2.5}$ in Kaohsiung and Taichung is industrial emissions and air masses traveling from Northern China (Chen et al., 2014). The most polluted areas in Fujian are coastal cities such as Quanzhou and Zhangzhou (Xu et al., 2013), with local pollution mainly attributed to transportation, industry, and inflows from outside areas. In order to acquire adequate monitoring data, a 50-km buffer around Fujian was created in this study.

2.2. Data

2.2.1. Data sources and processing

Daily mean $PM_{2.5}$ concentrations from 2005 to 2018 from 188 air quality monitors were collected from the China National Environmental Monitoring Center (http://www.pm25.in/), local Environmental Monitoring Centers of Xiamen city, Quanzhou City and Zhangzhou city in Fujian and Taiwan Environmental Protection Administration (https://airtw.epa.gov.tw). Additionally, we downloaded visibility data from 67 weather stations in our study domain through the National Centers for Environmental Information (NCEI) (Liu et al., 2017).

Multiple data products from Terra and Aqua satellites were utilized in our study. As illustrated in Supplementary Text S 1.1, we downloaded the MAIAC MODIS AOD product (MCD19A2) at 1 km resolution from NASA's Level-1 and Atmosphere Archive & Distribution System (https://ladsweb.modaps.eosdis.nasa.gov/) (Liang et al., 2018), daily cloud fraction product (Aqua and Terra Collection 6 Level 2 cloud products, MYD06_L2 and MOD06_L2) at 1 km resolution (https:// modis.gsfc.nasa.gov/) (Bi et al., 2019), and MODIS Fire/Hotspot data from the Fire Information for Resource Management System (FIRMS, https://earthdata.nasa.gov/earth-observation-data/near-realtime/

firms) (Huang et al., 2018). We obtained the Normalized Difference Vegetation Index (NDVI) data from MODIS 1-month global NDVI dataset at 1 km resolution (MOD13A1). Digital elevation of 1 arc-second (~30 m) resolution was downloaded from Advanced Spaceborne

Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM).

The ERA5 (C3S, 2017) is the 5th generation re-analysis of European Center for Medium-Range Weather Forecast (ECMWF) for the global climate and weather. The ERA5 hourly dataset and monthly meteorological dataset (Contains modified Copernicus Climate Change Service Information [2005–2018]) at 31 km resolution were obtained for the AOD gap-filling and $PM_{2.5}$ prediction, respectively (Text S 1.2). Assimilated 3-hourly AOD data (Randles et al., 2017) was extracted from the Modern-Era Retrospective analysis for Research and Applications (MERRA, Version 2) and we calculate the averages of AOD values and hourly ERA5 meteorology data from 9:00 a.m. to 3:00 p.m. to match the satellite overpass time (Xiao et al., 2018). Moreover, MERRA $PM_{2.5}$ concentration was calculated based on five MERRA-2 simulated $PM_{2.5}$ species including black carbon, sulfate, sea salt, organic carbon and dust (Provencal et al., 2017).

The land cover data for year 2005, 2008, 2010 and 2015 from the Chinese land use/land cover (CNLUCC, http://www.resdc.cn/) (Xu et al., 2018) data was used in this study. This high-resolution dataset was generated by supervised classification and visual image interpretation based on Landsat TM/ETM images. Road network information for year 2017 were obtained from the Google road map (http://www.bigemap.com/), while those of year 2010 were interpreted visually based on the Google Earth's satellite-photo images and road data in 2010. The UN WPP-Adjusted version of Gridded Population of the World (GPW) (Center for International Earth Science Information Network - CIESIN - Columbia University 2018) in 2005, 2010, 2015, and 2020 were linearly interpolated to calculate 1-km annual population density from 2005 to 2018.

Monthly means of all aforementioned daily datasets were calculated and we used the MAIAC 1-km grid to spatially align all datasets (Text S 1.3). The road length and the proportions of different land use categories were also calculated in each MAIAC Grid. We also calculated the fire spots counts of 20-km, 35-km, 50-km, and 75-km radius buffers in each month.

2.2.2. An overview of major air pollution control policies in Fujian and Taiwan

Several air pollution control policies have been implemented from 2005 to 2018 in the TSR (Table 1, Table S1). Early-stage environmental policies in Mainland China include the 11th (2006–2010) and 12th (2011–2015) Five-year Plan on Environmental Protection (11th and

12th FYP-EP) and simultaneous Energy Conservation and Emissions Reduction policies (i.e., 11th FYP-ECER and 12th FYP-ECER). For each national policy, Fujian also issued its corresponding provincial measures, i.e., 11th FJFYP-EP, 12th FJFYP-EP, 11th FJFYP-ECER, and 12th FJFYP-ECER. These policies used emission reduction rates of SO2, energy consumption, and NOx as their primary performance indicators. The 12th FYP on Air Pollution Prevention and Control in Key Regions (APPC-KR) was the first plan with air quality goals in Mainland China. From then on, with specific PM_{2.5} concentration goals and benchmark year, the Action Plan of Air Pollution Prevention and Control (APPC-AP) from 2013 to 2017 and the Three-year Action Plan aims for Blue Skies (3YAP-BS) from 2018 to 2020 as well as their corresponding local plans in Fujian (FJAPPC-AP and FJ3YAP-BS) were also implemented. Furthermore, amendments to the Law of the People's Republic of China on the Prevention and Control of Atmospherics Pollution (ALPRC-PCAP) were passed in 2015 and took effect in 2016. Fujian's control policies has gone through three stages, i.e., total emission control, air quality improvement, and finally economic and industrial restructuring (Ma et al., 2019). Overall, Fujian's policies still highly rely on specific and costly local actions (Wong and Karplus, 2017).

Taiwan began to monitor PM2.5 concentrations in 2005, but control policies have not kept up with monitoring due to concerns of their potential impact on the economy (Liu, 2018). Control policies before 2014 include the 7th and 8th amendments to the Air Pollution Control Act (7th AAPCA and 8th AAPCA), amendments on standards for the sulfur content of automobile gasoline and diesel fuels (ASSAG and ASSAD) and the 5th emission standard of diesel and gasoline vehicles (5th ESDGV). Stronger air pollution policies were implemented after 2014 such as the Innovative PM2.5 Control Strategies (IPCS) and Clean Air Action Plans (CAAP), the 14 + N Air Pollution Control Strategy (14 + N APCS) and Air Pollution Control Action Plan (APCAP). Additionally, the 9th Amendments of Air Pollution Control Act (9th AAPCA) was issued to guarantee the application of two aforementioned policies. As may be concluded from Supplementary Table S1, there was an upward trend in the stringency of Taiwan's policies, especially regarding air-pollutant emission standards from industrial and vehicle sources as well as emission reduction measures (Chen et al., 2019; Lin et al., 2018). Unlike the policies in Fujian, Taiwan's policies rely significantly on economic incentives and considers public feedbacks.

2.3. Methods

2.3.1. AOD gap-filling modeling

Since satellite-retrieved AOD has non-random missingness due to cloud cover, directly averaging available daily AOD values to derive monthly means likely introduces biases into this important predictor of PM_{2.5}. Following Bi et al. (2019), we developed a random forest (RF) model to fill the AOD data gap at the daily level before calculating monthly averages. RF model can utilize bootstrapped dataset and randomly select a subset of the predictors at each node results in constructing wide variety of trees. In this model, we incorporated predictors of MERRA AOD, cloud fraction, humidity, temperature and coordinates of the grid centroids in our RF gap-filling model (S 2.1). We adopted the method of three-rolling day samples for the middle day model proposed by Bi et al. (2019). Instead of using the full dataset, we randomly sampled 10,000 grid cells with predicted PM_{2.5} levels each day to speed up model training (if there are less than 10,000 grid cells available on a given day, all the samples were retained).

2.3.2. PM_{2.5} prediction modeling

We developed a random forest model to estimate monthly mean $PM_{2.5}$ concentrations with predictors such as monthly mean gap-filled AOD, land use variables, meteorological parameters, population density, visibility and fire spots (S 2.2). We also built a model without AOD to examine the impact of gap-filled AOD on the prediction of $PM_{2.5}$ concentrations. We used 10-fold temporal and spatial cross-validation

(CV) techniques in the full domain and in Fujian and Taiwan separately to evaluate model performance.

2.3.3. Policy efficacy evaluation

Using model-predicted PM_{2.5} annual average concentrations as the dependent variable, we developed a multivariate linear regression model to evaluate the effect of the policies implemented in Fujian and Taiwan separately. The independent variables include land use variables (percentage of forest, developed land and length of main roads), meteorological parameters (temperature, surface pressure, wind speed PBLH, surface albedo, total cloud cover, CAPE and precipitation), and the policies implemented in Fujian and Taiwan (Table 1). We included meteorological parameters in this model to account for their impact on the interannual variabilities of PM2.5 levels. Policies that were implemented during the same time periods or followed the same framework were combined to one binary indicator variable. For instance, the APPC-KP, 12th FYP-EP, 12th FYP-ECER and their corresponding provincial measures in Fujian were all designed based on the 12th Five-Year Plan, and the actual start time of these policies were all in 2012, hence we combined those policies into one variable. Our policy evaluation model is as follows:

$$\begin{split} PM_{2.5q,y} &= \beta_0 + \beta_1 T_{q,y} + \beta_2 RH_{q,y} + \beta_3 Si_{10q,y} + \beta_4 Fal_{q,y} + \beta_5 SP_{q,y} \\ &+ \beta_6 TCC_{q,y} + \beta_7 Pop_{q,y} + \beta_8 RoadSum_{q,y} + \beta_9 Developed_{q,y} \\ &+ \beta_{10} Forest_{q,y} + \beta_{11} Policy_{1q,y} + \beta_{12} Policy_{2q,y} + \beta_{13} Policy_{3q,y}... \\ &+ \beta_n Policy_{nq,y} + \varepsilon_{q,y} \end{split}$$
(1)

where $PM_{2.5q,y}$ is the PM_{2.5} annual concentration at grid cell q of year y (1,994,258 and 1,567,020 predictions for Fujian and Taiwan, respectively); β_0 is the intercept term; β_1 to β_n denote the location specific slopes in year y; $T_{q,y}$, $RH_{q,y}$, $Si_{10q,y}$, $Fal_{q,y}$, $SP_{q,y}$ and $TCC_{q,y}$ are the annual mean temperature, relative humidity, wind speed, albedo, surface pressure and total cloud cover at grid cell q in year y respectively; $Pop_{q,y}$ is population density; $RoadSum_{q,y}$, $Developed_{q,y}$ and $Forest_{q,y}$ are the length of all roads and the percentage of developed land and forest; and $\varepsilon_{q,y}$ is the error term; $Policy_{1,...,n}$ represents implementation situation of each policy at grid cell q in year y. This model was also built for each land-use type (developed land, forest, farmland and grass) separately.

3. Results

3.1. Performance of PM_{2.5} prediction model

There were 16,540 observations in our training dataset, including 12,389 in Taiwan and 4151 in Fujian. For Taiwan, the lowest monthly PM_{2.5} concentration occurred in Pingtung in June 2016 ($2.3\mu g/m^3$), while the highest was in December 2007 in Kaohsiung (94.7 $\mu g/m^3$). PM_{2.5} concentration in the west of the Taiwan island is much higher than in the east. The lowest and highest monthly observations in Fujian are 6.07 $\mu g/m^3$ near Zhangzhou in September 2017 and 86.4 $\mu g/m^3$ in Tongan in August 2015. Generally, the PM_{2.5} measurement in the economically advanced southeastern seaboard is higher than the inland hilly area in Fujian. When assessed together, the TSR is a less polluted region compared to the rest of China, but its PM_{2.5} concentration is three times that of the United States (Hu et al., 2017).

Our AOD gap-filling models (Text S Eq. (2)) resulted in mean OOB R^2 values of 0.94 and 0.95 for Terra and Aqua AOD, respectively. We then averaged gap-filled monthly mean Terra and Aqua AOD as a predictor as Text S Eq. (3) to estimate 1-km monthly PM_{2.5} concentrations. The overall CV, spatial CV and temporal CV R^2 s of the prediction model were 0.89, 0.83 and 0.82, respectively (Fig. S1 (a), Fig. S2 (a), Fig. S2 (b)). In addition, the RPE and RMSE for monthly PM_{2.5} predictions were 15% and 4.4 µg /m³, respectively, indicating good agreement between model predictions and ground measurements. Fig. S1 (b) shows the variable importance rankings for the predictors in



Fig. 2. Spatial distributions of annual mean $PM_{2.5}$ concentrations from 2005 to 2018.

model. Year, visibility, AOD, surface albedo and NDVI were the top-five important predictors for monthly $PM_{2.5}$ concentrations. Furthermore, the spatial CV $R^{2}s$ for Taiwan and Fujian were 0.85 and 0.73, respectively, and the temporal CV were 0.86 and 0.66, respectively (see Fig. S2).

3.2. PM_{2.5} spatial and temporal trends in TSR from 2005 to 2018

According to the predicted annual mean $PM_{2.5}$ in the TSR (Fig. 2.), no significant trends in $PM_{2.5}$ concentrations were observed in Fujian during 2005–2011, but the years of 2007 and 2009 experienced elevated $PM_{2.5}$ levels of 32.46 µg/m³ and 30.98 µg/m³, respectively. In this period, major Taiwanese cities in the southwest such as Tainan, Kaohsiung and Taichung, showed a slight decrease in $PM_{2.5}$ concentration while a slight upward trend was found in southeastern Taiwan (i.e. Hualian city).

Dramatic reductions in PM_{2.5} took place in the TSR after 2012. PM_{2.5} levels in Taiwan dropped ~7 µg/m³ in the period of 2012–2016 and then plateaued during 2016–2018. Conversely, for Fujian, there was a notable drop in PM_{2.5} concentrations of ~4 µg/m³ in 2012, followed by a slight increase of 0.8 µg/m³ between 2012 and 2014, and then a significant decrease of ~5 µg/m³ from 2015 to 2018. As shown in Supplementary Fig. S3, annual variation rate with linear regression in each grid was applied to identify the overall trends from 2005 to 2018. We noticed that PM_{2.5} pollution level of all areas in the TSR showed a decreasing trend with yearly mean of 14 years decreasing by 12.07 µg/m³ and *p*-values for most areas below 0.005. Specifically, the PM_{2.5} level at southern Taiwan and inland suburban areas of Fujian has relatively stable variation than that at the hot pots include western Taiwan and the coastal zone and urban inland section of Fujian.

In terms of spatial distribution, industrialized cities and city clusters have higher $PM_{2.5}$ concentrations in the TSR. The most polluted cities of Fujian are coastal cities including Putian, Zhangzhou, Quanzhou, and Xiamen and northwestern Sanming next to Jiangxi Province. The highest $PM_{2.5}$ levels are in western Taiwan, with Kaohsiung and Taichung having the most serious air pollution. Minimum $PM_{2.5}$ levels were found in Longyan of Fujian, and Taitung and Hualien of Taiwan. The spatial distribution and temporal variation trends in the annual $PM_{2.5}$ concentration of the TSR showed in Fig. 2 is consistent with ground monitor measurements, validating our model's predictive power. Supplementary Fig. S4 showed that Xiamen's city center has higher concentration than the central park covered by forest (purple polygon), demonstrating the value of our high-resolution prediction model in resolving fine-scale spatial $PM_{2.5}$ gradients in the study domain.

3.3. Performance of policy evaluation model

The regression coefficients of each policy variable with PM2.5 concentration for the whole domain and separated by land-use types were extracted from the evaluation model of Fujian and Taiwan policies. Fig. 3. shows that all the control policies implemented in Fujian and Taiwan are significantly negatively correlated with PM_{2.5} concentrations, indicating that all had some effectiveness for PM2.5 control. As indicated by the mean regression coefficients ($-5.63 \ \mu g/m^3$ for the entire policy implementation period), the CAAP is the most effective control policy for Taiwan. It is worth noting that there is a disparity of policy effectiveness on PM2.5 concentration of four land-use types which becomes greater when the policy is more effective. It can be seen from Fig. 3 that most Taiwan policies have been more effective on developed land than the other land-use types. This is consistent with the above-mentioned finding that the decline of PM_{2.5} concentration is larger in urban areas. 3YAP-BS and APPC-AP, along with their implementations, had the two greatest negative coefficients with -7.7and -4.13 respectively, therefore are the most effective policies in Fujian. The disparity of policies effectiveness on different land-use types has also occurred in Fujian, yet much less notable when compared to Taiwan.

A comparison of the temporal variations of annual mean $PM_{2.5}$ concentration (APC) and annual mean population weighted $PM_{2.5}$



Fig. 3. Regression coefficients of Fujian and Taiwan policies on different land-use types.





Fig. 4. PM_{2.5} trends from 2005 to 2018, and corresponding air pollution control policies.

concentration (PAPC) as well as the control policies implemented from 2005 to 2018 are presented in Fig. 4. In general, the trends of APC and PAPC in both Taiwan and Fujian are consistent with the implementation of different policies. Based on the implementation periods and the temporal trends of $PM_{2.5}$ concentration, we could observe four main change stages for both Fujian and Taiwan.

In phase 1 for Fujian (2005–2010), $PM_{2.5}$ levels decreased slightly from 2005 to 2006, increased in 2007, then decreased consistently.

There were no emission control goals before the release of 11th FYP for National and Fujian's Economic and Social Development of China in 2006. Not until later in 2007 was the Comprehensive Working Plan on ECER launched, mainly aiming at reducing sulfur dioxide (the precursor gas of particle sulfate). As a result, notable improvements were observed at the end of 11th FYP from 2007 on (i.e. total reduction of 8.1% and 6.4% during Phase 1 of APC and PAPC). Phase 2 (2011–2015) started with fluctuating $PM_{2.5}$ levels between 2010 and 2014 followed

by a significant reduction after 2014 (7.0% reduction in APC and 7.4% reduction in PAPC for whole phase 2). The National and Fujian provincial ECER policies during FYP-12 as well as FYP-11 both had limited effect on PM2.5 control given the complex mixture of PM2.5 and limited effectiveness of emission control. The 12th FYP on APPC-KR of Fujian was basically consistent with the Fujian's ECER policy and did not have an obvious immediate effect on Fujian's APC and PAPC although the APPC-KR still proved to be effective in other heavily polluted regions of Mainland China (Ma et al., 2019). With the joint effort with APPC-AP in 2013 and its implementation rules for Fujian in 2014, Fujian's APC and PAPC finally began to fall, reaching 10-year lows of 26.2 μ g/m³ and 29.1 μ m³ respectively. The APC and PAPC plummeted in the third phase (2014-2017) due to APPC-AP in 2013 and the implementation rules of APPC-AP further reduced PM2.5 levels by 12.8% for APC and 16.8% for PAPC in whole phase 3, exceeding the PM2.5 reduction targets of APPC-AP. Meanwhile, the ALPRC-PCAP was implemented in 2016 to strengthen existing of policies. Downward trends in PM_{2.5} concentration continued in the fourth phase (2018~) with reductions of 5.8% for APC and 6.8% for PAPC in 2018 alone, mainly attributed to the implementation of 3YAP-BS in Fujian and fulfilling the PM2.5 deduction goal ahead.

There were no ambient air quality standards or specific control measures for PM2.5 in Taiwan in phase 1 (2005-2011, total reduction of APC and PAPC are 2.5% and 9.8%). However, the decline may have been caused by the launch or revision of several emission standards on stationary and mobile sources. Under the implementation of two amendments of the Air Pollution Control Act, especially the 7th amendment, PM2.5 concentration continued its decline in phase 2 (2011-2013, total reduction of APC and PAPC are 8.8% and 7.4%). Dramatic reductions in the 3rd phase (2013-2014, total reduction of APC and PAPC are 11.7% and 14.3%) may be attributed to the IPCS. The last phase 4 (2015-2018, total reduction of APC and PAPC are 14.2% and 19.6%) had the most significant drop in the last 14 years. This was especially pronounced from 2015 to 2017 (total reduction of APC and PAPC are 18.5% and 17.7%) due to the CAAP. From 2017 to 2018, the launch of 14 + N APCS, APCAP and the 9th AAPCA did not have immediately detectable effects on the PM2.5 concentration (APC increased 5.4%, PAPC decreased 2.4%) probably due to the lag effects of policy.

Overall, the reductions of APC and PAPC in Taiwan are 9.21 μ g/m³ and 14.95 μ g/m³ (total reductions of APC and PAPC are 32.6% and 42.5%), which are larger than that of Fujian, with 7.80 μ g/m³ and 9.07 μ g/m³ (total reductions of APC and PAPC are 25.4% and 27%). A substantial difference between APC and PAPC for Taiwan and Fujian has been that policies in Taiwan were slanted towards residential areas while Fujian's policies have relatively consistent effects on PM_{2.5} levels across the region.

4. Discussion

4.1. Comparison with PM_{2.5} models in previous studies

The RF model developed for Fujian and Taiwan at 1 km resolution in this study resulted in a higher R² value (0.89) and a lower RMSE value (4.55 μ g/m³) than the models from previous coastal studies (Chu and Bilal, 2019; He et al., 2018; Jung et al., 2018; Wu et al., 2018; Xiao et al., 2017; Yang et al., 2019). Ma et al. (2019) develop a 2-stage statistical model to estimate PM_{2.5} concentrations in China from 2004 to 2017. They reported that the PAPC of Fujian in 2010 and 2015 were 34.48 μ g/m³ and 29.22 μ g/m³ respectively, in excellent agreement with our predictions of 34.48 μ g/m³ and 29.10 μ g/m³. The APC trend in Taiwan from 2006 to 2013 predicted by our model is also consistent with that predicted by Wu et al. (2018). Moreover, according to The Working Paper of RSPRC (Zhou et al., 2018b), the annual PM_{2.5} concentration in Taiwan decreased by 17% from 20 μ g/m³ in 2012 to 15 μ g/m³ in 2017, which is also close to our predicted rate (17.5%). Nevertheless, compared to the study of Ma et al. (2016) and Wu et al. (2018), we applied an advanced machine learning model with more ground $PM_{2.5}$ measurements and more important variables such as full-coverage gap-filled AOD. In addition, our model reveals that year is the most significant predictor since the emissions of $PM_{2.5}$ and its precursors changed over time under various control policies. The accurate long-term predictions provided by previous studies (Jung et al., 2018; Ma et al., 2019) at spatial resolution of 10 km or 0.1 degree are not able to accurately evaluate control policies at both fine spatial and temporal resolution. Therefore, our long-term, high resolution model could be a valuable tool for policy assessment.

4.2. Comparison of the control policies in Fujian and Taiwan

Ma et al. (2019) reported consistency in long-term trends between satellite-derived PM2.5 concentrations and the implementation of various air pollution control measures in Mainland China (Huang et al., 2018; Xue et al., 2019). Instead of evaluating existing policies though simulated PM2.5 concentration under different policy scenarios, our policy evaluation model has taken advantage of well-calibrated satellite-derived PM2.5 concentrations to assess the overall effects of various air pollution control policies during their implementation periods. Change rate indicators of air pollution concentration, which have been used in previous studies to represent the effectiveness of control policies (Cai et al., 2018; Cheng et al., 2019), were also applied in the evaluation. Since the total change rate of APC and PAPC in Taiwan is greater, the overall air pollution control policies in Taiwan seem to be more effective to lower PM_{2.5} concentration than those in Fujian. Nevertheless, the control policies of Fujian in recent years such as the APPC-AP, FJAPPC-AP, 3YAP-BS and FJ3YAP-BS have also resulted in significant declines of $\mathrm{PM}_{2.5}$ concentrations. Compared to previous policies, they have mainly focused on enhancing energy-saving and emission-reduction approaches, consistent with the other parts of Mainland China (Gao et al., 2019). For example, the 3YAP-BS intensified the optimization and adjustment of industrial and energy systems to promote low-emission development in Mainland China. Aside from controls for industries with high energy consumption and high pollution, elimination of backward production capacity and coal consumption control, 3YAP-BS has emphasized developing green industries and set goals for the proportion of low-carbon and efficient energy consumption (15%).

At present, the CAAP have proved to be the most effective controls in Taiwan by our policy evaluation model. Apart from enhancing energy-saving and emissions-reduction approaches, it also put major focus on the legal system, economic incentives, and public participation. The economic incentives considered were for stationary pollution sources, the travel industry, and an air pollution prevention fee rate – these were implemented with the support of Taiwan's Air Pollution Control Act. With regards to public participation, measures concerning messaging on agriculture, transportation and culture can also be found in the clean air plans.

The current approach in Fujian has had immediate effects on the reduction of PM_{2.5} concentrations, but it does not solve the long-term issue of weak local policy monitoring, evaluation and enforcement. The main reason may be the misalignment of incentives as highly specific and costly local actions are needed in these polices, but funds are centrally allocated (Wong and Karplus, 2017). Additionally, such command and control approaches as mandatory output reduction ought not to be implemented for a long time as the high economy-wide cost of industrial structural adjustment can be harmful to corporate emission reduction initiatives (Li et al., 2019). Based on the responses in Taiwan, early introduction of market-based approaches could be beneficial because they can be an excellent tool to steer the industry towards sustainability (Li et al., 2019). In the future, Fujian's policies would need to ensure incentive compatibility at the local levels through a reworking of political, fiscal and organizational mechanisms that support

implementation (Wong and Karplus, 2017). Moreover, according to Wang et al. (2019), while the present willingness to pay for air pollution treatment is weak in Mainland China, it could be higher if more satisfactory public participation measures were enacted and practiced. While treatment measures are needed, Tong et al. (2019) reported that even the most advanced end-of-pipe technologies have limited effects on $\ensuremath{\text{PM}_{2.5}}$ control, and that stringent energy and industrial structure adjustment could benefit both air quality improvement and economic development. On the other hand, Taiwan may need to consider more policies for improving its low-carbon and efficient energy consumption as well as industrial structure adjustment. To minimize the economic and social costs of control policies, joint regional control coordination mechanisms is essential. The TSR could work together to conduct research on industrial structure adjustment and using new low-carbon and efficient energy to accelerate the elimination of backward production capacity and reduce coal consumption (Gao et al., 2019). It should be noted that in addition to environmental policies, changing weather patterns and other economic policies could also affect the patterns of PM_{2.5}. We included various meteorological predictors in our model to separate the contributions of meteorological factors to the interannual variabilities of PM2.5 levels. Although many of the air pollution control policies involved industrial and economic restructuring, it is difficult to separate the impact of other economic policies being enforced in conjunction with the environmental policies, which is a limitation of our study.

4.3. Spatial heterogeneity of effectiveness for control policies in Taiwan

Ambient PM_{2.5} pollution can have a significant negative impact on the overall growth and yield of crops including wheat and corn (Rai, 2016; Zhou et al., 2018). Although plants may possess some stresstolerant mechanisms, a considerable amount of damage can happen to them as a result of PM or dust deposition leading to inhibition of photosynthetic activities and protein synthesis as well as increased susceptibility to injuries caused by microorganisms and insects. Therefore, controlling PM_{2.5} over agricultural regions is important. However, despite the downward trend from 2005 to 2018 there was uneven effectiveness depending on land-use type, especially for Taiwan. Even though Taiwan and Fujian both implemented pollution control acts such as agricultural waste smoke emission control, the effect of control policies in Fujian is shown to be more evenly distributed than that of Taiwan. Much of this discrepancy may be attributed to the difference in the enforcement of control policies and topography regarding the two regions. To limit the damage of air pollution on agriculture and ecosystems, especially for the farmland and forest which are close to the industrial area, effective long-term strategies for controlling PM_{2.5} in Taiwan must be developed. For example, it has been suggested that policy and financial incentives to enterprises producing serious pollution in areas with large tracts of arable land should be applied to minimize contamination of the atmosphere (Zhou et al., 2018a).

4.4. Influential factors of PM2.5 changes in the TSR

The spatial distribution of $PM_{2.5}$ we found in the TSR is very similar to that found by previous studies (He et al., 2018; Wu et al., 2018). Northern Fujian is characterized by more hills, extensive vegetation coverage, and few human activities, resulting in lower $PM_{2.5}$ levels. In contrast, as reported by Xu et al. (2013) and Wu et al. (2019), the high $PM_{2.5}$ pollution in southern coastal cities has been caused by the interactions among coal combustion, pyrometallurgical processes, traffic emissions, sea salt, and crustal sources.

The eastern regions with low $PM_{2.5}$ level in Taiwan mostly consist of mountains running from the northern to southern tip. The major urban areas in Taiwan are in the western regions with flat to gently rolling plains. Most heavy-metal industrial parks are located in the

southcentral part of the island, giving rise to ambient $PM_{2.5}$ levels. Previous studies indicated that the major sources of $PM_{2.5}$ in Taiwan are industrial emissions and long-range transport of pollutants from Chinese mainland (Chen et al., 2014; Wang et al., 2016; Wu et al., 2018). The transported haze events from Chinese mainland over Northern Taiwan in winter have been extensively studied, but the longterm effects remained unclear due to the lack of long-term monthly average $PM_{2.5}$ measurements for both Taiwan and Chinese mainland.

In this study, monthly average PM2.5 concentration of Northern China, Northeastern China and the YRD produced by Xiao et al. (2018) and Ma et al. (2016) as well as the PM_{2.5} concentrations in Taiwan from September to May of 2005 to 2017 (a period dominated by northeasterly winds), were used to evaluate the long-term transport from China's polluted areas to Taiwan (Chuang et al., 2018). The correlation coefficients between the monthly average PM_{2.5} concentration of three highly polluted areas in China and Taiwan are 0.17, 0.27 and 0.25, respectively, indicating that the correlation is low. Consistency of trends in yearly PM2.5 concentrations between the high polluted regions of Mainland China and Taiwan was also not found in this study. Some previous studies reported that the majority of PM_{2.5} in Taiwan can be attributed to local emissions from traffic and industrial activities (Chen et al., 2001; Gugamsetty et al., 2012; Hsu et al., 2016; Lu et al., 2016; Tseng, 2016), while others suggested that changes in daily PM_{2.5} levels in Taiwan may be due to long-range transport from the aforementioned regions. The impact of long-range transport at the monthly and longer time scales needs to be further investigated.

5. Conclusion

In this study, we developed a RF model with gap-filled satellite AOD and other predictors to estimate high-resolution ground-level PM_{2.5} concentration in the TSR from 2005 to 2018. Based on its predictions, the effectiveness of air pollution control measures and actions in TSR was evaluated quantitatively. By analytically comparing the policies implemented in TSR, we concluded that Fujian's policies could take more advantages of market-based approaches and public participation measures, while Taiwan's policies can focus more on improving its lowcarbon and efficient energy consumption. Furthermore, since Taiwan's control policies exhibited obvious spatial heterogeneity of effectiveness, all land-use types should be taken into consideration for new policies given the potential harm of PM2.5 to agricultural production, food security and ecosystems. The disagreement between monthly PM_{2.5} concentration patterns in the highly polluted regions of Mainland China and Taiwan suggests that the transport mechanism at monthly and longer time scales needs to be further studied. Finally, several policies are still under implementation as of our current study, which warrants future analysis on their overall impact on regional air quality.

One limitation of this study is that since the specific emission data for TSR can't be obtained yet, more accurate regional concentration data can not be predicted. Since the actual starting and ending times and specific reaction periods of these control policies are not recorded in the policy documents or any studies, the lag effect of policies is hard to be controlled in the policy evaluation model. As Taiwan has more ground measurements and more evenly distributed monitoring sites, the accuracy of predicted $PM_{2.5}$ in Taiwan is expected to be higher than Fujian. This implies that the accuracy of policy efficacy evaluation is also higher in Taiwan, which is another limitation of our study. In addition, several policies are still under implementation and we can only analyze their effectiveness of their current implementation period. Future study will focus on fully evaluating those policies based on a longer period of regional $PM_{2.5}$ concentration estimates.

Declaration of Competing Interest

None.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.rse.2020.112067.

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