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Human Activity Affects Forest Fires: The Impact of Anthropogenic Factors on the Density of Forest Fires in Poland

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Abstract: Forest fires, due to climate change, are a growing threat to human life, health, and property, especially in temperate climates. Unfortunately, the impact of individual factors on forest fires varies, depending on the geographical region and its natural and socio-economic conditions. The latter are rarely introduced into fire warning systems, which significantly reduces their effectiveness. Therefore, the main goal of this study was to quantify the impact of a wide range of anthropogenic factors on forest fires, using Poland as a representative example of a Central European country. Data were analyzed in relation to districts for the period 2007–2017, using correlation analysis and regression modeling applying global and local/mixed regression methods. It was found that almost all of the 28 variables taken for analysis significantly determined the density of forest fires, but the greatest role was played by the length of the border between forests and built-up areas, and road density. In addition, the impact of most of the analyzed variables on forest fires varied over the study area, so implementing non-stationarity in geographically weighted regression models significantly improved the goodness-of-fit compared to global models.

Keywords: forest fires; anthropopressure; socioeconomic factors; spatial non-stationarity; geographically weighted regression; Poland

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1. Introduction

Wildfires, one of the main disturbances to forest ecosystems [1], can cause huge economic, environmental, and social losses. Annually, circa 10 million hectares of worldwide forests are damaged to varying degrees [2]. In Europe, the Middle East, and Africa, over a million hectares of forest are burned annually, including several hundred to several thousand hectares of forests in Poland, in an average of 7.5 thousand fires per year [3]. It is estimated that in 2000–2013 the total fire losses in Poland amounted to 480 million PLN [4], which is around EUR 110 million. Fires cause changes that negatively affect the environment, such as decreases in biodiversity, changes in water regimes, changes in soil geochemical properties, and changes in the microclimate. In turn, the negative effects in the social sphere include not only the risk of death or danger to health, but also psychological stress and damage to, and loss of, property, all of which may lead to a deterioration in the quality of life [4]. Due to the fact that the number of forest fires has been increasing [5–9], the identification of the factors influencing forest fires is an urgent need and a serious challenge, especially as these phenomena may intensify in tandem with socio-economic development [10]. This makes it all the more important to separate human-caused factors from natural causes.

The analysis of the influence of anthropogenic factors on forest fires has been undertaken by many researchers, and the importance of this type of research is demonstrated by the fact that human activity causes up to 90% of fires in the world [11]. As [12] stated in South Korea, since most forest fires are linked to human activity, socioeconomic factors are critical for estimating their probability. The influence of human activity on the fire regime is clearly visible from at least the Neolithic age [13]. In a cause-and-effect analysis of forest fires, various anthropogenic factors may reflect various aspects of human activity. Reference [14] found that the neighborhood effect (which means that each area affects, and is affected by, its surrounding areas) is of great importance in the spreading of fires, and that the proximity of buildings and roads has a significant positive influence on the occurrence of fires. The authors of [15] included road density and population density in a fire index, reasoning that forest roads are potential paths of human-caused fire spread. The greater the human activity and the greater human access to the forest, the greater the risk of forest fires breaking out. This was confirmed by [16], who analyzed road and rail density, distance to the city, population density, proportion of seasonal units, and proportion of owner-occupied units. The results showed that the areas with higher population density and higher road density positively influenced the occurrence of fires. Moreover, they found that the factors significantly influencing fire occurrence on one spatial scale were often also significant on the other scale (the study was conducted in two analytical grids: 5-km square and 10-km square cells), with no factor or group of factors clearly dominant; the fires were related to a combination of factors [16].

While the above research was based on the analysis of fires as discrete (point) data, a different approach was adopted by [17], who confirmed that the probability of forest fires depends, among other things, on the distance to various types of infrastructure (negative relationship). The distance to roads was also included in forecasting systems as reclassified raster layers [18,19]. Anthropogenic factors, e.g., proximity to settlement units [20] and the distance to cities and roads [21], are also elements of the existing forecasting systems based on various fire hazard indexes.

However, [22] found that roads had little impact on fires. The authors explained this, first, by an extensive road network in the study area that did not provide clear spatial trends, and second, by the adopted method of representation; the distance to roads was more significant when related to the location of the fire's ignition. When fires were modeled with kernel density, the significance of road distance was lower. Therefore, the authors emphasized that the analysis of road density may be a better approach for studying road's relationship with fire density. On the other hand, in Arizona, it was shown that the probability of a fire is inversely proportional to the density of the road network [23]; the opposite of the results from other studies. However, in that particular study, the majority (66.7%) of the analyzed fires were caused by lightning, and not by humans, which could have strongly affected the results. Similar findings were reported in studies from Spain [24], which showed that the distribution of fires was strongly related to human access to the natural landscape, more specifically to the proximity of urban areas and roads, which were considered the most important fire causation factors. Reference [25] analyzed the relationship between forest fire density (1987–2001) in forest administrative units and external factors in Jilin Province, China. The results showed that topography was the most important contributor to forest fire ignition, followed by anthropogenic factors. The authors of [26] studied the structure of socio-economic dynamics as well as environmental characteristics at a municipal level and found that they are crucial for a better understanding of the local spatial patterns of forest fires in the Mediterranean region.

Socio-economic factors are as important as buildings or road networks, due to the presence of humans and their activities influencing the occurrence of fires [27]. By analyzing the direct causes of forest fires using data collected by firefighting services, [28,29] stated that any fire forecasting system should also consider the socio-economic causes of fires. Such studies were carried out with multiple regression analysis [30], using EUROSTAT statistics on production by sector or social statistics (unemployment rate, population size), at a provincial level. The authors of [31] included recreational areas, population changes, and the unemployment rate in their research as factors that increase interpersonal conflict, and thus, positively influence the risk of a fire starting. Reference [32] showed that although the main factor influencing the occurrence of fires in Portugal is the forest type, there are intra-forest differences; within the same habitat type there are differences closely related to socio-economic conditions, such as depressed zones which are more vulnerable to fire occurrence due to high levels of emigration. Reference [33] identified a dozen anthropogenic variables affecting the number of fires per unit area in Spanish municipalities, including the density of agricultural machinery, the density of agricultural properties, the number of animals kept with traditional grazing, the percentage of unemployed, decline in the population associated with the abandonment of agriculture, socio-economic changes in urban areas, density of the road and rail network, intensification of agriculture, increased human presence, percentage of municipal land in protected areas, and, finally, deforestation. In southern Europe the unemployment rate, the density of livestock, and the density of local roads had a significant impact, but weaker than the meteorological or topographical conditions [34].

Most Mediterranean regions are highly vulnerable to extensive forest fires, and in some cases socio-economic factors (such as the percentage of local permanent population, tourists, pets, buildings) are key determinants [35], which is reflected in the classification of fire causes [3]. The authors of [36] used the concept of "economic stress", which was defined by many variables, such as unemployment, poor education, racial segregation, overcrowding (the number of occupants per m^2 in an apartment), and family demographics. Potentially, high unemployment or a difficult financial and social situation may increase the risk of forest fire, not only in cities or villages, but also in their immediate vicinity.

Based on the above-mentioned studies, differences in the importance of individual anthropogenic factors on the density of forest fires, depending on the geographical location, can be noticed. Reference [37] stated that ongoing research showed that it may not be possible to directly apply a fire risk model that is successful in one region to other regions. Nevertheless, the non-stationarity of the influence of external anthropogenic factors on forest fires has so far not been sufficiently taken into account. Geographically weighted regression (GWR) is rarely used in fire research [38] and has only been introduced in a few cases, e.g., by [39–41].

In Central Europe the variables taken into account in forest fire analyses are mainly natural, i.e., meteorological (e.g., [42–45]), geological, and topographical [42], and those related to the combustive character of material, such as fuel moisture (e.g., [45]). In Poland, the influence of anthropogenic factors on the occurrence of forest fires has not yet been analyzed in detail. Research and work has focused on the effectiveness of firefighting operations and rapid response procedures in the event of a fire, rather than accurately identifying all predictors. According to the Polish National Forest Fire Information System (NFFIS) [46], most fires break out as a result of direct and indirect human activity. Therefore, it is crucial to extract, identify, and quantify the anthropogenic factors affecting the occurrence of fires in Polish forests, which is the main goal of this study. To achieve this, the following specific goals were defined: (a) identification of anthropogenic factors that significantly determine the occurrence of forest fires; (b) specification of regression models, with testing for potential spatial non-stationarity; (c) determination of the temporal variability or stability of the relationship between anthropogenic variables and the occurrence of forest fires.

All these goals will help verify the following hypotheses:

Hypothesis 1. *The key anthropogenic factors influencing the growing density of forest fires in Poland are their increasing number and their close proximity to buildings and transport infrastructure.*

Hypothesis 2. *The influence of other anthropogenic factors (e.g., social and demographic) on the increasing number of fires is significant, but secondary to the variables related to infrastructure and buildings.*

Hypothesis 3. *The relationships between the indicators quantifying human activity and the occurrence of forest fires vary in space, so the influence of anthropogenic factors on forest fires in Poland is non-stationary.*

2. Materials and Methods

2.1. Study Area

This research covered the area of Poland, a country located in Central Europe, with an area of approximately 312,700 km^2 and a population of about 37.7 million people. (Figure 1). The decision to conduct analyses on a national scale was dictated by access to homogeneous input databases, both on forest fires and on elements of the geographical environment, enabling studies on a number of factors potentially affecting the occurrence of forest fires and taking into account their possible spatially variable influence on fire density. At the same time it allowed us to omit factors that are very difficult to measure, resulting from the existing legal system (e.g., fire regulations), and organizational and institutional solutions (e.g., public services responsible for fire protection, forest management, etc.), which are transferred into fire prevention practices [47]. In Poland, these are regulated at the national level [48] and therefore do not affect the studied phenomenon in space.

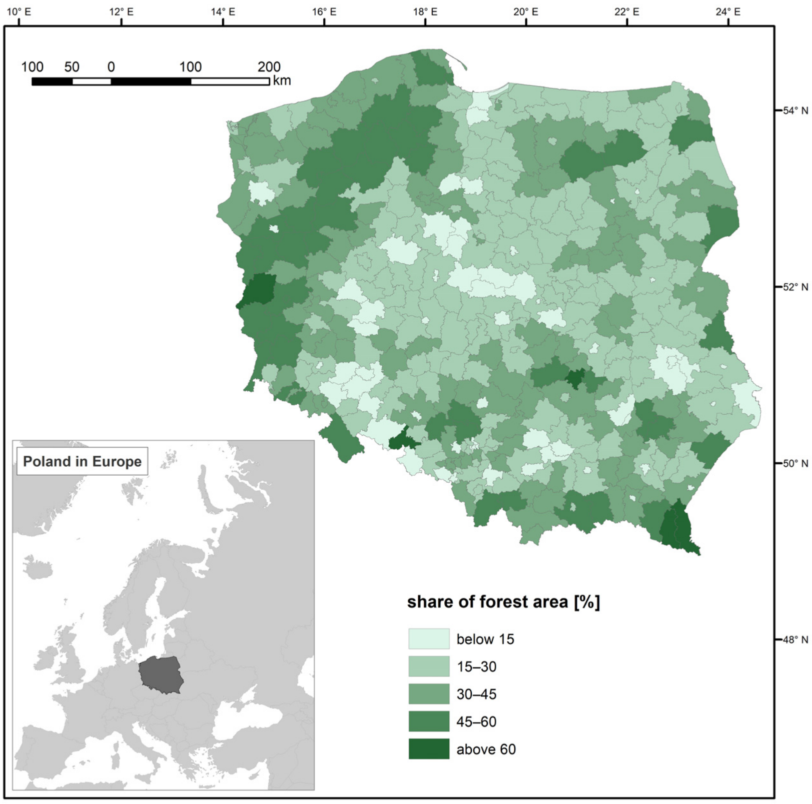

Figure 1. Study area: forest cover in Polish districts. Inside box: Poland against the backdrop of Europe.

The forest cover in Poland, calculated according to the international standard in 2017 [49], amounts to 30.9% and is slightly lower than the European average (32.8%). The forest distribution in Poland is relatively uneven (Figure 1), most forests have been preserved in the south of the country in the mountains (Sudetes and Carpathians), in the northern lakelands, and in western Poland. Central Poland is characterized by the least amount of forest cover (Figure 1). The highest forest cover (over 74%) is observed in the Bieszczady Mountains (SE Poland), while some districts that are more than half forested lie in the Lubuskie Region (W Poland) and the western lakeland districts (Figure 2). The lowest (<15%) forest cover is typical for districts in central Poland and urban districts in southern and south western parts of Poland (Figure 2). The distribution of forests in Poland is related to agriculture, urbanization and industry, historical factors, and natural conditions (climatic, hydrographic, and topographic), and forests are found mainly in areas with the least valuable soils. The distribution of fire events in the period 2007–2017 was also uneven and does not fully correspond to the distribution of forests in Poland (Figure 2).

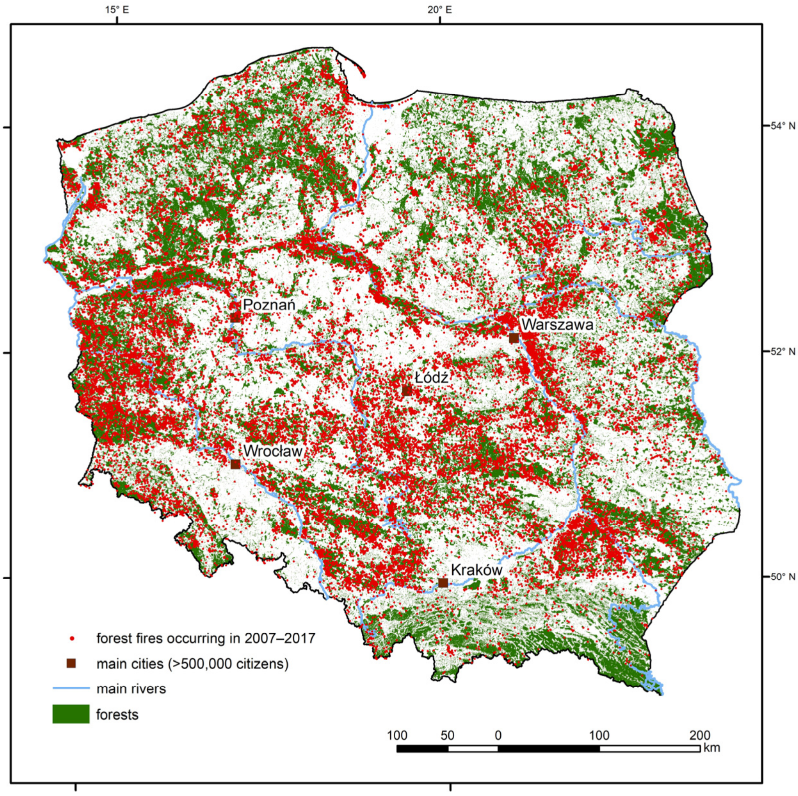

Figure 2. Study area: forest fires (2007–2017) in relation to selected elements of the geographical environment of Poland.

The population distribution is also uneven, resulting from diverse natural conditions, a changing political and economic situation (partitions, wars), border changes, migration actions, and the policy of industrialization during the socialist period. The most densely-populated area (apart from large cities) is triangular-shaped, with its base lying along the southern country border and its apex near the mouth of the Wisła. It is related to economic development, which was concentrated in the southern and central parts of Poland. Sparsely populated areas are mainly large forest complexes in the lakelands, at the western border, and in the easternmost mountain areas, where there are few towns and the rural population prevails, which results in a low average population density in these areas. With regard to districts, cities with district rights (urban districts) are the most densely populated. The density of the railway network increases from NE to SW Poland, while the road network is the most developed in south-western, southern, and central Poland, and the lowest road density is typically in the eastern and north-western parts of the country [50].

2.2. Anthropogenic Factors Potentially Related to Forest Fires

The influence of anthropogenic factors on forest fires can be analyzed in two ways; in relation to fire events treated as points or in relation to their number per area unit. For area-level analyses, the reference unit used may be a grid network [13,14,29] or administrative units [30,33,51,52]. The first area-related approach may obtain more accurate results, unfortunately it cannot be applied for many socio-economic variables, because these statistics are usually compiled for administrative units.

Due to the uneven distribution of forests in Poland, the analyzed variable in this study was the density of forest fires (i.e., the number of fires per square kilometer of forest area), not their number. This phenomenon was analyzed in relation to Polish districts (n = 380), the second order of national administrative units. The choice of this reference level resulted mainly from the availability of socioeconomic data; moreover, an analysis of the subject literature showed that some researchers (e.g., [33,38]) also used this approach in their studies.

Fire data for the period 2007–2017 were taken from the Polish National Forest Fire Information System [46] and initially cleaned of incorrect records. The data come from fire reports collected by firefighters and in the period 2007–2017 over 38,000 forest fires were registered [46] (Figure 2). According to this database, the main cause of fires in Poland is direct and indirect human activity: arson (caused by adults and minors), neglect (including burning vegetation, burning waste, throwing cigarette butts), and accidents (related to electricity transmission, road or rail transport, or industrial activity). As a result, potential predictors were selected to constitute a representation of various manifestations of human activity in geographical space. Based on the literature analysis discussed in the Introduction and the availability of data, the following groups of variables were selected: (1) buildings data; (2) road and rail infrastructure-related indicators; (3) demographic data; (4) economic indicators; (5) additional indicators, i.e., heating, density of electricity lines, and share of illegal landfills (Table 1). Each of these groups reflects various human behaviors and can represent how a fire hazard arises in the forest environment.

Table 1. Potential determinants of forest fires analyzed in the study.

Manifestation of Human Activity	Factors (Acronyms for Variables)
Buildings and land use	Share of total district area (%): • residential buildings (BURES) • tourist buildings/hotels (BUTOUR) • agriculture/industrial buildings (BUIND) • public and other buildings (BUOTHER) Length of contact boundaries (m/km^2): • contact boundaries between forests and residential areas in relation to district area (BOUFORRES) • contact boundaries between forests and industrial areas in relation to district area (BOUFORIND)
Transport	Density of transport lines running through forests (length in meters per square kilometer of forest): • highways and express roads (ROADHIGH) • main or commune roads (ROADMAIN) • local roads (ROADLOC) • secondary roads (ROADSEC) • non-electrified (RAILNEL) and electrified (RAILEL) railroads
Demography	• level of demographic burden (number of people in post-working age in relation to number of people of working age) (DEMBUR) • population density (persons per square kilometer) (DENS) • population density in the urban area (persons per square kilometer) (DENSURB)
Economy	• number of economic entities per 1000 residents (ECENT) • number of families benefiting from social public services per person (ESPS) • number of registered unemployed per total population (EUNEMPL) • number of people at pre-working (EPREWORK), working (EWORK), and post-working (EPOSTWORK) age in relation to the whole population • number of vehicles per square kilometer of district area (EVEHICS)
Other	• number of forest parking lots per square kilometer of forest area (OPARKL) • density of electricity lines running through forests (m/km^2) (OELINES) • percentage of houses with central heating installations in cities (OHEATCIT) and villages (OHEATVIL) • number of illegal landfills per square kilometer (OLANDFILL) • number of crimes against property in relation to district population (OCRIM)

The data on buildings indirectly reflect the places with the greatest spatial human activity [53,54]. The following categories of buildings were taken into account: residential, tourist, agriculture/industrial, and public buildings. The second group of indicators concerns linear elements of transport infrastructure (roads, railroads) related to mass human movement, which also significantly increase fire risk, e.g., by significantly increasing the spatial accessibility of the forest area for a larger number of people, or the risk related to the use of motor vehicles or road accidents. The third group, demographic indicators, included the share of population age groups characterized by relatively higher spatial mobility (demographic burden) and population density indicators reflecting the general and potential level of human pressure [55].

On the other hand, the fourth group of economic indicators is indirectly related to factors potentially increasing fire risk, such as spatial mobility and the possibility of fire ignition related to the number of cars, spatial mobility related to economic activity, and the age structure of the population. One should also consider here arson and neglect, which are important direct causes of forest fires, and which may result from the intensification of pathological phenomena (and which have their causes, among other things, in unemployment or social exclusion), which was confirmed, among others by [56].

The last group, other indicators, concerns selected phenomena accompanying factors increasing fire risk. In this case, we can indicate the spatial mobility related to the penetration of forest space (forest parking), the impact of selected elements of infrastructure (electricity pylons and power lines running through forests), existing sources of residential heating or illegal landfills that are potential sources of fire, as well as the intensity of certain social pathological phenomena (crimes against property) potentially related to arson and neglect. The remaining factors are potentially associated with the increased penetration of forests by humans and, indirectly, the level of wealth. Considering social factors, it is important to emphasize that human activities are very variable in time and space, which complicates the estimation of specific spatial patterns. This is also due to the fact that relevant temporal and spatial data are very difficult to collect, including the lack of accurate data on human activities in forest lands [33]. Some of the potential predictors (grass burning, recreation) were not included, due to the lack of relevant data. This made it necessary to use indicators indirectly related to forest fire risk. The data were obtained from two public external sources: (1) infrastructure data (i.e., rail and road network, buildings, electricity lines) and forest data came from the national Database of Topographic Objects, called BDOT10k and shared by the Head Office of Geodesy and Cartography [57]; (2) socio-economic data for the district level came from the Local Data Bank (called BDL), shared by the Statistics Poland office [58]. Infrastructure data were trimmed to the district boundaries, and the values of socio-economic indicators were calculated both for the areas of the districts and the forest areas in individual districts. All spatial analyses was performed with the EPSG: 2180 ("PUWG1992") projection using ArcMap and QGIS software.

2.3. Statistical Analysis

Due to the identified errors in the BDOT10k data for one district, it was removed from the dataset and all analyses were conducted on the remaining 379 units. The statistical analysis included: correlation analysis, linear regression analysis (univariate and multivariate), and geographically weighted regression analysis (both uni- and multivariate). Linear regression (LR) models were used to describe the relationship between the dependent variable (here: forest fire density) and independent variable(-s) (here: anthropogenic indices) [59]. LR can be considered a global technique, because it does not explore any local relationships between variables.

We also used geographically weighted regression (GWR), which is a method for exploring non-stationary (i.e., spatially differentiated) relations, and useful when global statistics do not represent local conditions. In GWR, all coefficients of independent variables vary depending on the location and parameter estimates take into account the spatial proximity to the specific location under consideration. Data from observations close to the considered location are weighted more heavily than data from distant observations [60]. GWR can also be univariate or multivariate. When some of the variables in the GWR model were stationary, we employed a mixed GWR model (MGWR) [60].

The spatial variability test in geographically weighted regression analysis was based on the Diff of Criterion value, which shows the difference between the global (LR) model and the GWR model. If the GWR model has a better fit with observations, the "Diff-Criterion" value is negative [61]. In addition, the specification of the GWR model included the selection of the kernel, i.e., the size of the neighborhood, which is responsible for how the point influence decreases with increasing distance from it. In this study an adaptive kernel was used due to the fact that Polish districts vary in size and shape.

There are several universal measures that assess the quality (goodness-of-fit) of the regression models considered in this study. For both LR and GWR, the coefficient of determination (R^2) about the degree of explanation of the variability by the model, while in the GWR model, apart from the global value of the coefficient (as in LR), local R^2 is also calculated for individual locations. The same situation applies to local values of standard error of the estimate, SE (sigma estimate). The most reliable indicator deciding which model, global or local, is better suited is the Akaike Information Criterion (AIC); the lower its value, the better the model [62].

Assessment of the statistical significance of differences between global and local/mixed models was based on mean absolute error (MAE) as the main diagnostic measure, used together with MAE error bars. This can be done by comparing the variation of MAE error bars. The model with the smallest MAE can be considered as performing best, only if its MAE error bar does not overlay the MAE error bar of any other model for the same case. The error bar was determined as MAE $\pm$ σMAE, where σMAE was the error of MAE calculation [63].

In the first step, correlation matrices (for individual years and for the 2007–2017 period) were used to investigate the internal relationships across the dataset. Then, for each anthropogenic variable, we used univariate LR and univariate GWR for the entire 2007–2017 period. These models were built in order to investigate the causal relationship of variables with fire density in Polish districts over the entire period, as well as to test the spatial stationarity of these relations.

Due to the fact that some anthropogenic variables were strongly correlated with variables reflecting similar aspects of human activity, the next step was to reduce their number by a stepwise elimination, on the basis of the r* critical value, calculated from the correlation matrices and t-Student critical values table [64]. Representatives of each group of factors were selected in such a way that they were strongly correlated with the density of forest fires, and such that at the same time they were not correlated with factors from other groups. The reduction of the number of variables was made on the basis of correlation matrices for the entire period and for individual years.

Then, for the period 2007–2017 and for individual years, multiple linear regression (MLR) models were specified through forward stepwise selection, each time based on a reduced set of variables. In each case, the dependent variable was the fire density in districts. Multivariate GWR models were built based on the same set of variables as the corresponding MLR models, and then local and global models were compared using adjusted R^2, AIC, and SE values.

It seems that from a practical point of view, that in prognostic models it would be advisable to constantly use a specified set of the same anthropogenic variables. Thus, an additional step in the analysis was to build complementary multivariate regression models for two selected variables, BOUFORIND and ROADLOC. These variables were selected because in the previous step they turned out to be the most frequent inputs to the models. Therefore, it was decided to check whether these two variables also built statistically significant models (global and local) in other years and how their diagnostic measures changed compared to the measures of other models. The R^2, AIC, and SE values were compared, as well as MAE and MAE errors.

The observations and predictions, as well as residuals and local adjusted R^2 (adj R^2) values for the whole period (2007–2017) were presented on the maps. Statistical analyses were conducted using Statistica 13.1 and GWR4 software.

3. Results

3.1. Correlation and Regression Analysis of Individual Variables

The correlation with forest fire density for the whole period (2007–2017) was significant ($p < 0.05$) for the vast majority (23 out of 28) of anthropogenic variables. Only five variables did not show any significant correlation with the forest fire phenomenon. These were: the density of secondary roads in forests, level of demographic burden, number of families using social assistance, number of forest parking lots, and number of illegal landfills (Table 2). The range of Pearson′s correlation coefficient r for significant variables varied (in absolute terms) from 0.1 to almost 0.65. In each group representing a different aspect of human activity there were variables significantly correlated with the density of forest fires. The most strongly correlated (>0.4) were individual representatives of buildings and land use (BOUFORIND, r = 0.65), demography (DENS, r = 0.41), economy (EVEHICS, r = 0.41), and others (OHEATVIL, r = −0.42). The group of transport-related variables was characterized by lower r values than the others (Table 2).

For all variables significantly correlated with forest fire density, the global regression results were also significant. The analyzed individual variables explained the variance of fire density in a range from less than 1% to 41%. (Table 2). For almost every group of factors (except the rail and roads group), it was possible to distinguish variables with a strongly dominant value of R^2. Such representatives were: BOUFORIND (R^2 = 0.41), ROADLOC and ROADMAIN (R^2 was very low here, approximately 0.05–0.06), DENS and EVEHICS (both 0.15), and OHEATVIL (0.17). Comparing the univariate GWR and LR models, it was found that the relationship between almost all auxiliary variables and forest fire density was spatially differentiated. Only the impact of the EUNEMPL and the ESPS were not found to have had a stationary nature (positive Diff-Criterion value). Taking into account spatial non-stationarity increased the level of explanation in the univariate models in every case, even by several times. For some of the variables, this improvement was exceptionally high, e.g., for BUTOUR (the R^2 value increased from 0.07 in LR to 0.63 in GWR); in other cases the increase was usually by three or four times. Generally, local models were characterized by a clearly higher level of explained variability of forest fire density than the respective global models.

We also checked the level of the correlation (r) and tested for the spatial non-stationarity of all considered variables and the density of forest fires in individual years (Supplementary Materials). The correlation coefficients fluctuated significantly between the different years. BOUFORIND had a clearly higher r-value (0.4–0.6) than the others factors in this group (except in 2015) (Figure S1). In the Road and Rail group, the r-value for ROADMAIN and ROADLOC had the highest values (Figure S2). The r-value for DENS showed a downward trend over the years (Figure S3). In the last two groups, the highest r-values were recorded for EVEHICS, OELINES, and OHEATVIL (Figures S4 and S5). The spatial non-stationarity of the relationship between the independent variables and the density of forest fires was a largely unchanging property during the 2007–2017 period, the exception being all transport variables and some of the economic and other variables (EUNEMPL, ESPS, OPARKL, OLANDFILL) (Figures S9 and S10), which fluctuated between negative values (non-stationarity process) and positive values (stationarity). The BOUFORRES, BOUFORIND, ROADLOC and variables from the demography group were subject to large fluctuations in r-value (Figures S6–S8).

Table 2. Results of statistical analysis for the relationship of single independent variables with forest fires for the 2007–2017 period.

Acronym	r Value (* if $p < 0.05$)	adj R^2 LR	adj R^2 GWR	Value of Diff-Criterion
		Buildings and land use		
BOUFORIND	0.646 *	0.414	0.685	−172.118
BURES	0.384 *	0.137	0.423	−87.777
BUIND	0.368 *	0.126	0.312	−36.057
BUOTHER	0.320 *	0.093	0.310	−43.862
BOUFORRES	0.321 *	0.098	0.418	−100.919
BUTOUR	0.272 *	0.067	0.628	−277.936
		Roads and rail		
ROADLOC	0.246 *	0.056	0.211	−26.218
ROADMAIN	0.244 *	0.053	0.244	−44.493
RAILEL	0.207 *	0.037	0.210	−26.962
RAILNEL	0.177 *	0.026	0.051	−0.869
ROADHIGH	0.101 *	0.005	0.049	−1.008
ROADSEC	0.100	0.005	0.223	−49.549
		Demography		
DENS	0.407 *	0.154	0.596	−217.538
DENSURB	0.348 *	0.112	0.490	−134.125
DEMBUR	0.038	−0.004	0.313	−140.611
		Economy		
EVEHICS	0.406 *	0.154	0.571	−196.747
ECENT	0.242 *	0.053	0.407	−113.998
EPREWORK	−0.239 *	0.051	0.287	−245.487
EWORK	0.165 *	0.022	0.349	−2878.183
EPOSTWORK	0.115 *	0.008	0.239	−127.190
EUNEMPL	−0.102 *	0.005	0.016	2.564
ESPS	−0.096	0.004	0.015	2.780
		Other		
OHEATVIL	−0.417 *	0.165	0.605	−218.045
OELINES	0.308 *	0.089	0.310	−62.636
OCRIM	0.205 *	0.037	0.337	−82.835
OHEATCIT	0.140 *	0.014	0.218	−89.240
OPARKL	0.055	−0.003	0.241	−53.436
OLANDFILL	0.034	−0.004	0.115	−0.940

3.2. Multivariate Models

The correlations between variables within particular groups were often very high, even over 0.9. The reduction in the number of variables allowed for the specification of the simplest, non-collinear multivariate regression models with the highest possible predictive power. All multivariate GWR or MGWR models (for the entire period and for individual years) were better suited than global ones. This was confirmed by comparing adjusted R^2, AIC values, standard errors of estimation, and the ANOVA. The latter was performed to check whether the improvement of the GWR (or MGWR) over the MLR was statistically significant (Table 3).

Table 3. Comparison of global multivariate linear regression (MLR) models and local (GWR) or mixed (MGWR) geographically-weighted regression models. The sign "(−)" before the variable name means that the variable is negatively correlated with a dependent variable, stationary variables in MGWR are in bold. The order of variables illustrates the order of entry into the MLR model (stepwise regression with forward selection). The sign "(+)" means the improvement GWR/GWMR model compared to MLR model.

Period	Independent Variables	Adjusted R^2		AIC		Standard Error of Estimation		Significant Local/Mixed Model Improvement (According to ANOVA)	Model Selection
		MLR	GWR/MGWR	MLR	GWR/MGWR	MLR	GWR/MGWR		
2007–2017	*BOUFORIND; ROADLOC; OHEATCIT*	0.45	0.70	949.00	745.30	0.84	0.62	+	GWR
	BOUFORIND; ROADLOC	0.44	0.72	952.55	722.34	0.84	0.60	+	GWR
2007	*BOUFORIND; ROADLOC*	0.27	0.51	−470.38	−596.81	0.13	0.11	+	GWR
2008	*BOUFORIND; ROADLOC*	0.26	0.54	−216.80	−374.91	0.18	0.14	+	GWR
2009	*BOUFORIND; ROADLOC*	0.42	0.76	−423.31	−733.23	0.14	0.09	+	GWR
2010	*BOUFORIND; ROADLOC; ROADHIGH*	0.21	0.31	−779.25	−818.91	0.09	0.08	+	GWR
	BOUFORIND; ROADLOC	0.20	0.60	−775.12	−1009.82	0.09	0.06	+	GWR
2011	*BOUFORIND*	0.30	0.62	−183.21	−393.58	0.19	0.14	+	GWR
	BOUFORIND; ROADLOC	0.30	0.72	−182.86	−500.47	0.19	0.12	+	GWR
2012	*BOUFORIND; OLANDFILL; ROADLOC*	0.39	0.61	−406.42	−541.72	0.14	0.11	+	GWR
	BOUFORIND; ROADLOC	0.35	0.53	−378.31	−479.18	0.15	0.11	+	GWR
2013	*BOUFORIND; OHEATCIT2013;* ***ROADLOC***	0.18	0.37	−946.69	−1002.44	0.07	0.06	+	MGWR
	BOUFORIND; ***ROADLOC***	0.16	0.37	−942.43	−1022.72	0.07	0.06	+	MGWR
2014	*BOUFORIND; ROADLOC*	0.38	0.67	−689.66	−907.45	0.10	0.07	+	GWR

Variables abbreviations: *BOUFORIND*, contact boundaries between forests and industrial areas in relation to district area; *BOUFORRES*, contact boundaries between forests and residential areas in relation to district area; *ROADLOC*, local roads running through forests per forest area; *OHEATCIT*, percentage of houses with central heating installations in cities (for the whole period; in the case of 2013: *OHEATCIT2013*); *ROADHIGH*, highways and express roads inside forest areas; ESPS2015, number of families benefiting from social public services per person in 2015; *OLANDFILL*, number of illegal landfills per square kilometer; *RAILNEL*, non-electrified railroads inside forest area; *EUNEMPL*, unemployment rate.

Table 3. *Cont.*

Period	Independent Variables	Adjusted R^2		AIC		Standard Error of Estimation		Significant Local/Mixed Model Improvement (According to ANOVA)	Model Selection
		MLR	GWR/MGWR	MLR	GWR/MGWR	MLR	GWR/MGWR		
2015	*RAILNEL; BOUFORRES; ROADLOC; (-)EUNEMPL; ESPS2015*	0.19	0.33	−224.87	−284.63	0.18	0.16	+	GWR
	BOUFORIND; ROADLOC	0.14	0.35	−206.39	−292.19	0.18	0.16	+	GWR
2016	*BOUFORIND; ROADLOC; ROADHIGH*	0.23	0.38	−494.08	−568.03	0.13	0.11	+	GWR
	BOUFORIND; ROADLOC	0.21	0.64	−486.95	−752.31	0.13	0.09	+	GWR
2017	***BOUFORIND***; *ROADLOC*	0.17	0.56	−935.63	−1146.69	0.07	0.05	+	MGWR

Variables abbreviations: *BOUFORIND*, contact boundaries between forests and industrial areas in relation to district area; *BOUFORRES*, contact boundaries between forests and residential areas in relation to district area; *ROADLOC*, local roads running through forests per forest area; *OHEATCIT*, percentage of houses with central heating installations in cities (for the whole period; in the case of 2013: *OHEATCIT2013*); *ROADHIGH*, highways and express roads inside forest areas; ESPS2015, number of families benefiting from social public services per person in 2015; *OLANDFILL*, number of illegal landfills per square kilometer; *RAILNEL*, non-electrified railroads inside forest area; *EUNEMPL*, unemployment rate.

Local or mixed models raised the level of explanation of the forest fire density variance up to 70% or more; this was the case for the multiannual 2009 and 2011 models. The adjusted R^2 value of local models attained up to twice the R^2 value of the corresponding global models, and in almost every case it was higher by one-third (Table 3). Taking into account the non-stationarity of the process, this improved the model statistics (adj. R^2, estimation error, AIC) for all years. The models for 2013, 2015, and 2017 had the lowest MLR adjusted R^2 values, below 0.2.

In most cases, similar variables entered the model through stepwise selection, the most constant was BOUFORIND, building almost every model (except 2015). In addition, the variables frequently included in the models were roads running through forest areas (ROADLOC, ROADHIGH). Therefore, these two variables, BOUFORIND and ROADLOC, were chosen to build alternative models for some periods (in which a different set of variables was entered after Bartosiewicz selection). The most ephemeral variables turned out to be RAILEL, RAILNEL, ESPS, EUNEMPL, OHEATCIT, and OLANDFILL. The other variables did not enter any of the models.

Only in 2013, for ROADLOC, and in 2017, for BOUFORIND, was their impact not constant in the area of research; in the case of the other years, their impact varied depending on the location. In general, the order of entering the model (and therefore the strength of the influence of the variables on the density of forest fires in districts) in local and mixed models was identical to that in the global models.

In the case of multi-year models, there were no significant differences between the values of mean absolute errors (MAE) of the global model, selected as a result of stepwise selection, and the MAE values of the global model based on the two selected (BOUFORIND and ROADLOC) variables. The same was the case for the GWR models. At the same time, a significant decrease in MAE values could be seen between the respective GWR vs. MLR models (Figure 3).

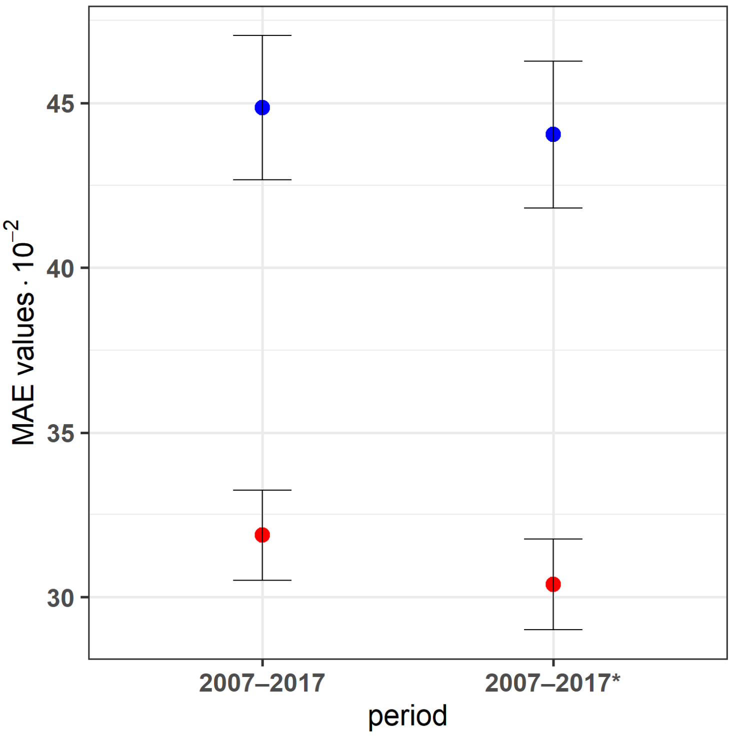

Figure 3. MAE values and MAE error bars for the 2007–2017 period. The asterisk means that the model was built on two selected variables (BOUFORIND and ROADLOC) and not based on the stepwise variables selection method. Note the units on the y-axis.

In the case of the one-year models (Figure 4), the situation was similar; no significant differences in MAE values between models based on stepwise selection and models based on two selected variables were noted. The lowest MAE values were recorded in 2010, 2013 (for both, regardless of the explanatory variables), and 2017. Almost all GWR models had significantly lower MAE values, except for 2010 and 2016.

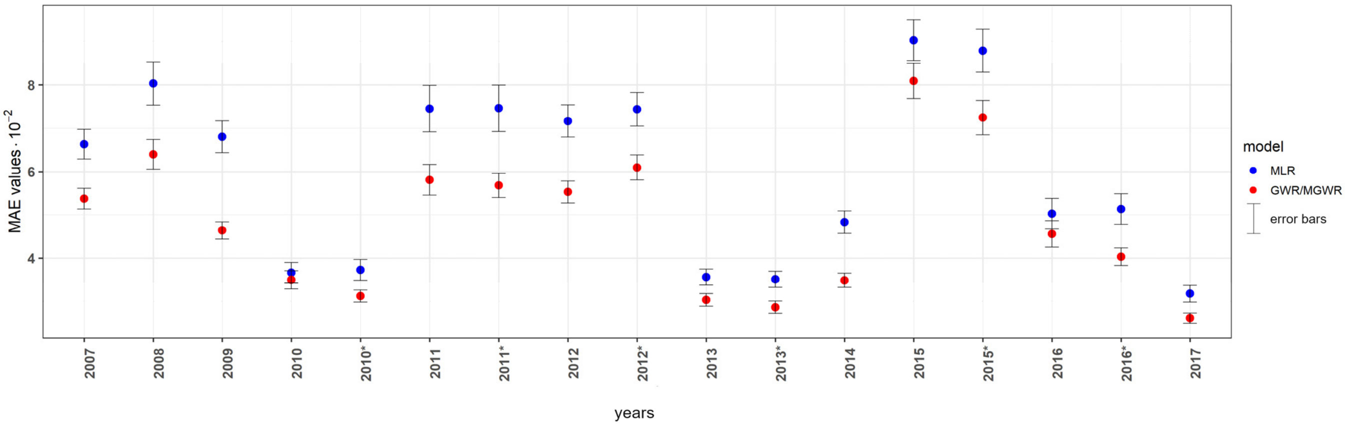

Figure 4. MAE values and MAE error bars for individual years. The asterisk means that the model was built on two selected variables (BOUFORIND and ROADLOC), and not based on the stepwise variable selection method. Note the units on the *y*-axis.

The differences in the density of forest fires between the observed and estimated values in each district are shown in Figure 5. The highest density of forest fires was observed in districts that are big cities, with the exception of the voivodeship cities (where these values were relatively low). Moreover, high values of forest fire density were observed in central Poland and the main industrial area in the southern part of the country. The lowest density of forest fires was found in the Carpathians and their foothills, in some districts on the eastern country border, and in north-eastern Poland (Figure 5a). The spatial distribution of the predicted values was similar to the observed ones, the nature of the distribution on a national scale was well recreated by the model (Figure 5b). The differences between the observed and predicted values mainly concerned the Carpathian region. Analyzing the values of the standardized residuals, it can be seen that the vast majority of districts (68.1%) were within the range −0.5 to 0.5 STD and 86.5% were within the range −1.0−1.0 STD. There were strongly underestimated values (<−2.5 STD) in six districts and strongly overestimated (>2.5 STD) values in 10 districts (Figure 5d). The magnitude of the local value of adjusted R^2 changed from the north east, where the model worked relatively well (0.71), to the south, where the model performed worst (0.22) (Figure 5c).

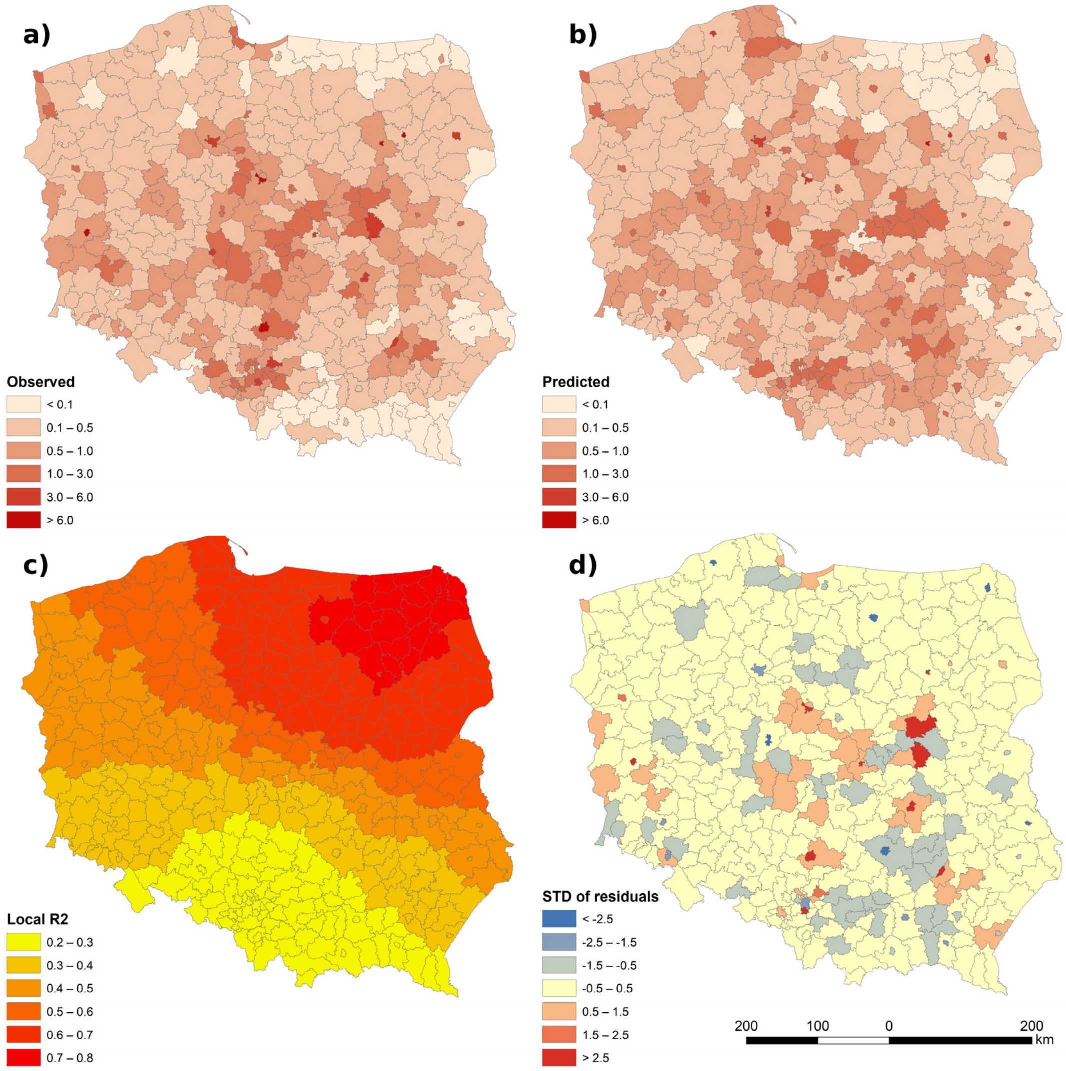

Figure 5. Spatial distribution of observed (**a**) and predicted (**b**) density of forest fires (number of fires per square kilometer of forest area), locally adjusted determination coefficients, R^2 (**c**), and standard deviations of regression residuals (**d**).

4. Discussion

The main goal of this study was to identify and quantify anthropogenic factors affecting the density of fires in Polish forests. The results of the above analyses show almost all the potential predictors selected for the study were found to have an impact on the density of forest fires in Polish districts. Moreover, in each group of factors reflecting various aspects of human presence and activity in a geographical space, there were variables significantly correlated with the density of forest fires. The obtained results indicate that the individual influence of the most significant representatives of each group of anthropogenic factors was relatively high, taking into account that the influence of unitary variables on a complicated natural phenomenon was considered; in four out of five groups, variables explaining around 60% of the local variability of fire density were identified.

While the global impact of these factors on fire density remained at a low level, taking into account the spatial differentiation of the impact in the study area reveals very strong relations. These results show that the influence of external factors is not constant in the area of research, and the strength of the impact varies depending on the location.

On average, variables related to the density of transport routes running through forests had the lowest R^2 values in the univariate local regression models. This may be due to the fact that roads are usually used for travel from one place to another, and the direct penetration of the forest environment by people instead occurs through internal forest paths, which were not included in the current analyses. This can be confirmed by the fact that the lowest, but nonetheless significant, correlation was found in the case of highways and expressways, which in Poland are most strongly separated from the intersected areas. Other road types are most often not isolated from forest areas in any way, and there is usually only a few meters wide strip of grass between the forest and the road. Moreover, on a district scale this relationship may not be as visible as on a much larger scale, which confirms the results obtained by [16]. The high values of GWR determination coefficient in the case of electrified railways can be explained by the high risk of transmitting a fire impulse (spark) from under the wheels of trains to forest areas; this was how the largest fire in Poland since World War II (and also the largest in Central Europe) broke out [48].

As shown by [17,20,21], the human environment is more susceptible to fire than forest areas located further away from buildings. This is probably why within the group related to buildings and land use, the highest adjusted R^2 was observed for the contact zones between the forest and industrial areas, the percentage of tourist buildings, and contact zones between the forest and residential areas (as an expression of the increased human pressure and the direct impact on the surrounding area, translating into a greater possibility of penetrating the forest environment).

Demographic factors related to general anthropogenic pressure, i.e., population density (the presence of people in a geographical space), are also important for forest fires. As [15] states, population density is a very important factor, as it affects the distribution of potential fire sources; the higher the population density, the greater the fire risk. Other researchers also came to similar conclusions [7,16,22,24,25,35], which is not surprising, considering that human activity is the direct cause of most fires.

Among the economic factors, the indicators related to the number of vehicles had the greatest impact; they primarily affect the increased mobility of people, including the penetration of forest areas. Entrepreneurship, expressed as the number of economic entities per 1000 inhabitants also proved to be important for the density of forest fires. Probably, this is an indicator that is indirectly but significantly related to the entire set of behaviors that translate into an increase in fire risk, e.g., increased mobility (of entrepreneurs, their customers), distribution, and density of potential sources of fire.

The positive correlation of forest fire density with the percentage of the working-age population and the negative correlation with the percentage of the pre-working age population is most likely related to the age of the most common direct perpetrators of fires; the [46] database shows that in the period 2007–2017 approximately 60% of fires started deliberately, i.e., arson, were started by adults.

Unlike [32] or [36], the unemployment rate did not have such a large impact on the density of forest fires, although it should be noted that it had been relatively low in Poland. This was accompanied by a significantly lower economic activity of the inhabitants than in other countries. As a result, the social profile (and thus spatial behavior) of the unemployed in Poland could be slightly different from the populations described in both mentioned studies.

In the case of other factors, the share of rural houses with central heating installations may indicate the economic level, which may affect the occurrence of fires, according to [32,36]. The impact of the remaining variables (density of electricity lines, number of crimes against property) can be explained by the unintentional transmission of a fire signal to the forest environment.

Factors that were found not to have a significant impact on forest fires were mainly those related to point objects and were relatively few (such as the number of illegal landfills or parking lots) or did not have such a clear impact on human activity (the amount of social assistance). On the district scale their impact may turn out to be negligible; at the same time, some of them increased the predictive power of local models. Therefore, it is possible that, in accordance with the conclusions of [16], when conducting analyses on a more detailed scale, their impact could become more visible.

Most anthropogenic factors are interrelated in various ways, therefore not all of the most significant representatives of individual groups were included in multivariate models. In addition, in the case of the multivariate models, the local or mixed were better fitted to observations than the global. In addition, the impact of some factors also varied over time; the variables included in the models were not identical for all years. In general, it can be stated that the impact of the length of contact border between forests and industrial areas is relatively constant, only in 2015 did this factor not enter the model. At the same time, in 2015 the local adjusted R^2 of the model was almost the lowest (0.33). Perhaps the reason for this was that in 2015 there were many more fires than in the remaining years (8292 according to [46]; more than twice the average for the period 2007–2017) and this could have influenced the results. Furthermore, in 2010, 2013, and 2016 the adjusted R^2 model was relatively low (below 0.4), but it was difficult to identify the reasons for this situation. Most likely, this could have been influenced by weather conditions that were not analyzed in this study. The variables concerning transport infrastructure were an almost equally constant factor over time; only in 2011 did they not enter the model. Both of the above factors, the density of roads and the density of the contact between industrial areas and forests, also built a perennial model. The remaining variables included in the models for particular years were more ephemeral, their signal was present only in some years. It is difficult to find a convincing explanation for the appearance of these variables in the models. The ephemeral nature of these variables may also have resulted from a number of causes that we were not able to verify empirically, e.g., what are the conditions for the formation of illegal landfills and the hidden landfill–fire relationships. Regarding the amount of social assistance, first, due to the volatility of regulations and various social transfers, the number of people using social assistance changes significantly [52], and the composition of the population covered by such support also changes [65]. The relationship of this indicator with fires is in line with the pattern found in the cited studies [32,36], indicating a unemployment–fire relationship.

However, the impact of the above-mentioned ephemeral variables was not clear enough for the models built on them to have a statistically significant performance improvement (based on MAE values) in relation to the models built on the most constant variables (the border between forest and industrial areas and the density of local roads running through forests). For this reason, for the possible future introduction of anthropogenic variables to the forest fire forecasting system, it is suggested to select only these two variables in order to simplify the calculations. This was confirmed by [66], whose results also indicated road accessibility and length of wildland–urban interfaces as relevant drivers of fire density. In addition, geographically weighted regression should be used in the forecasting system instead of global regression equations, which are now statutorily defined [67]. This is all the more important as the spatial pattern of fires is not constant over time [68].

What should be emphasized is the strong impact of non-stationarity on the degree of explanation of the relationship between forest fires and anthropogenic factors, both at the level of individual variables and when analyzing the combined effects of variables; similar results were also shown by [69]. At the same time, these spatially variable relationships are so complicated that they require further research at the local level, taking into account the socio-economic specificity and historical conditions of the regions. Therefore, it is difficult to unequivocally identify the causes of non-stationarity. The zonal character of the changes in the predictive power of the models is probably the result of the spatial variability of socio-economic phenomena in Poland. This could also be the cause of extreme positive values of regression residuals; this was almost exclusively the case in medium-sized cities with district status. Such cities are very often characterized by a much more developed communication network or a completely different building structure than the surrounding districts; all but three were in the years 1975–1998 capitals of former provinces (when there were 49 in Poland) and the development of their infrastructure was usually more intensive than in surrounding areas. At the same time they did not have such an impact on the surrounding areas as the present voivodeship cities (due to suburbanization processes that have been operating since the 1990s [70]. They amount to less than 5% of Polish districts, but it must be borne in mind that in such situations the model will work less efficiently than in most of the country. A minor point may be the reference level and the scale used in this study, which were pointed out by, among others, [16].

Further analyses are planned on a much more detailed scale, i.e., grids with a side length of several kilometers and also taking into account additional variables in the form of internal forest paths.

5. Conclusions

In conclusion, as expected, the anthropogenic factors most strongly influencing the density of forest fires in Polish districts were those related to transport infrastructure and built-up areas. At an individual relations level, the highest average correlation coefficients and R^2 of linear regression were typical for the group of factors related to buildings. The transport-related factors were characterized by weaker relations with the density of forest fires. Nevertheless, representatives of both groups were included in almost all multivariate regression models, which proves their dominant role in the increasing number of forest fires in Polish districts, and this allow us to positively verify the first research hypothesis (Section 1). It is likely that the remaining, unexplained part of the variability was due to natural conditions; meteorological, topographic, features of the combustible material itself, and others.

Almost all of the remaining anthropogenic factors were shown to have a significant influence on forest fire density, and although for some variables the individual impact was stronger than for buildings or transport infrastructure, these variables did not enter into the multivariate regression models, or were entered into only some of them. Ipso facto, the second hypothesis is also confirmed.

The comparison of global and local or mixed model statistics and diagnostic measures was consistent with the third hypothesis and showed the existence of non-stationary processes; the influence of almost all anthropogenic variables on forest fire density varied over the study area. The variability of these relationships in individual years was also noted.

The only insignificant factors turned out to be the lowest-order roads, level of demographic burden, number of families benefiting from social public services per capita, forest parking lots, and illegal landfills. However, this is probably the effect of the scale considered in this study; it is possible that analyses at a more detailed level would reveal the impact of these factors on the density of forest fires, in particular parking lots or illegal landfills.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/f12060728/s1, Figure S1. Values of Pearson's correlation coefficient (r) in Buildings and land use group, Figure S2. Values of Pearson's correlation coefficient (r) in Roads and rail group, Figure S3. Values of Pearson's correlation coefficient (r) in Demography group, Figure S4. Values of Pearson's correlation coefficient (r) in Economy group, Figure S5. Values of Pearson's correlation coefficient (r) in Other factors group, Figure S6. Spatial variability (Diff of Criterion values) in Buildings and land use group, Figure S7. Spatial variability (Diff of Criterion values) in Roads and rail group, Figure S8. Spatial variability (Diff of Criterion values) in Demography group, Figure S9. (a) and (b). Spatial variability (Diff of Criterion values) in Economy group, Figure S10. Spatial variability (Diff of Criterion values) in Other factors group.

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