EXPLORING THE RELATIONSHIP AMONG POTENTIAL EVAPOTRANSPIRATION, PRECIPITATION AND WILDFIRE RISK IN WESTERN UNITED STATES

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CONTENT

Exploring the Relation among Potential Evapotranspiration, Precipitation and Wildfire Risk in Western United States

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Abstract: Based on monthly potential evapotranspiration (PET), precipitation (P), the location of wildfire events and occurrence time of wildfire events during 2014 to 2017, the relationship among PET, P and wildfire risk has been explored. PET, P and wildfire events during 2014 to 2016 were used to build a model. To verify whether the relationship was acceptable, 6 risk levels were confirmed by the normal distribution for both PET and P during 2014 to 2016. Risk-level 1 is the highest level, and risk-level 6 is the lowest level. To test this model, wildfire events from 2017, a year not used in model development, were compared to predicted 2017 risk level. Results show that wildfire events in 2017 can be predicted successfully during May to September since over 60.0% of wildfire events were identified in risk-level-1 area. The wildfire events that occurred in January, February, March, November and December can hardly be identified in risk-level-1 in this project, but those wildfire events occurred in the place where the risk level was 4.

1. Introduction

The effects of wildfires are numerous and wide-ranging, and they affect the economy, environment and so forth. Human beings may not only lose their property but also lose their home. The reasons which cause a wildfire vary. Nature such as lava and lightning can cause a wildfire, and human beings, the main cause of wildfires in US, is also the reason which cannot be neglected. From this aspect, people should be aware of the area, which may exist a high risk of wildfires, to remind people preparing well to avoid the damage in property and people's life. Issues such as less P, high evaporation and high land surface temperature may provide an appropriate situation for wildfire. Based on the previous researches, scholars(Westerling et al. 2003)-(Mo et al. 2006) have found there is a relation between Palmer Drought Severity Index (PDSI) and wildfire. But the relation is blurred. Besides, the way to calculate the PDSI highly depends on the quality of raw data. Whether the results can present the wildfire risk can hardly be identified. Modeling, such as FSPro, FARSITE and WFAS, is an effective way to predict the wildfire risk(Andrews, Finney, and Fischetti 2007), but modeling highly requites the quality of input data, such as weather data, and the modeling process takes time. Whether there is a simple way to efficiently predict the wildfire risk in a short time is the main goal for this project.

As fuel availability is the base for wildfire events, the western part of USA is the main area(BRUNSON and SHINDLER 2004) where wildfires occur. In Figure 1, it is easy to get the conclusion by searching where the wildfire occurs: wildfire strongly relates to the place where there are dense forest(Andrews, Finney, and Fischetti 2007). Based on this principle, the exact study area has been set in the western part of USA.

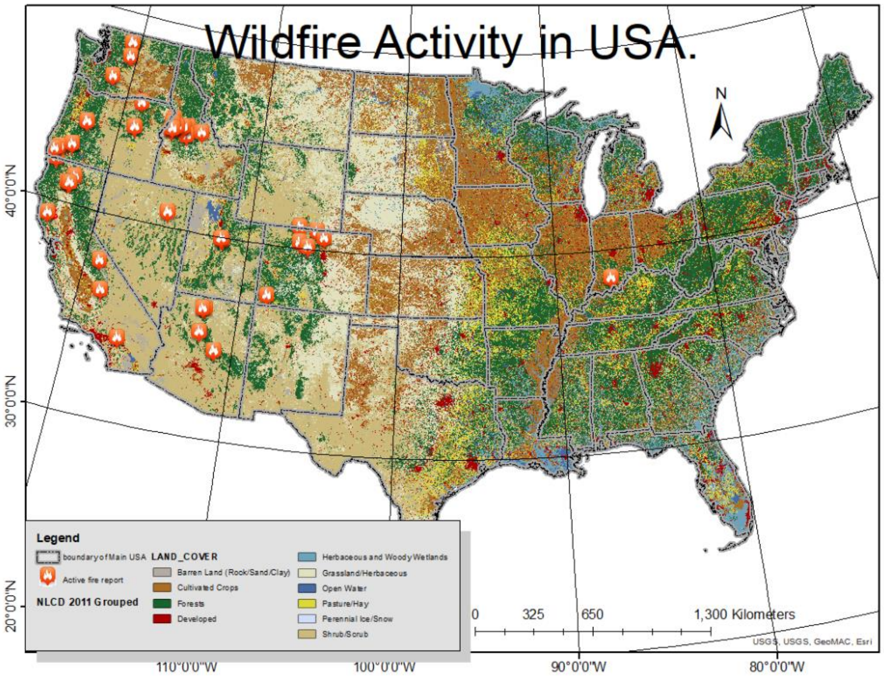


Figure 1 Wildfire Activity in USA (USA Wildfire Activity, data modified in Sep 20th, 2017)

2. Methodology and Data

(1) Methodology

PET is defined as the amount of evaporation that would occur if a sufficient water sources were available, and the value swayed by surface and air temperatures, insolation, and wind. Therefore, hot weather condition with strong wind can result in a bigger PET than that with cool weather condition. In the case that PET is very large, wildfire risk might be high. P is a significant source for surface and underground water. The humidity would be large when there is plenty of P, and in this case, wildfire risk might be low.

Similar to Budyko's idea, which has achieved iconic status in hydrology for its concise and accurate representation of the relationship between annual evapotranspiration and long-term-average water and energy balance at catchment scales(Sposito, Sposito, and Garrison 2017), a relationship among PET, P and wildfire risk has been assumed: under hot-dry condition where PET is high and P is low, wildfire risk is high; under cool-wet condition where PET is low and P is high, wildfire risk is low. By statistical analyzing toward PET and P during wildfire events under monthly scale from 2014 to 2016, the relationship among PET, P and wildfire risk will be concluded. Based on this relationship, the wildfire risk in 2017 will be predicted and verified.

(2) Data

Monthly P and PET during 2014 to 2017 have been downloaded from Land Data Assimilation Systems (https://ldas.gsfc.nasa.gov/). The format is NC file. The resolution of each data resources is 0.125°×0.125°. The unit for each parameter is millimeter. Small black points in Figure 2 represents the sites where meteorological data can be gathered.

Wildfire data has been downloaded from National Fire and Aviation Management (https://fam.nwcg.gov/fam-web/). The downloaded dataset contains the geological information (latitude and longitude) about wildfire events during 2014 to 2017, and the time when the wildfire occurred. All wildfire events occurred during this period have been pointed out in Figure 3. The distribution is consistent with the distribution of forest in Figure 1.

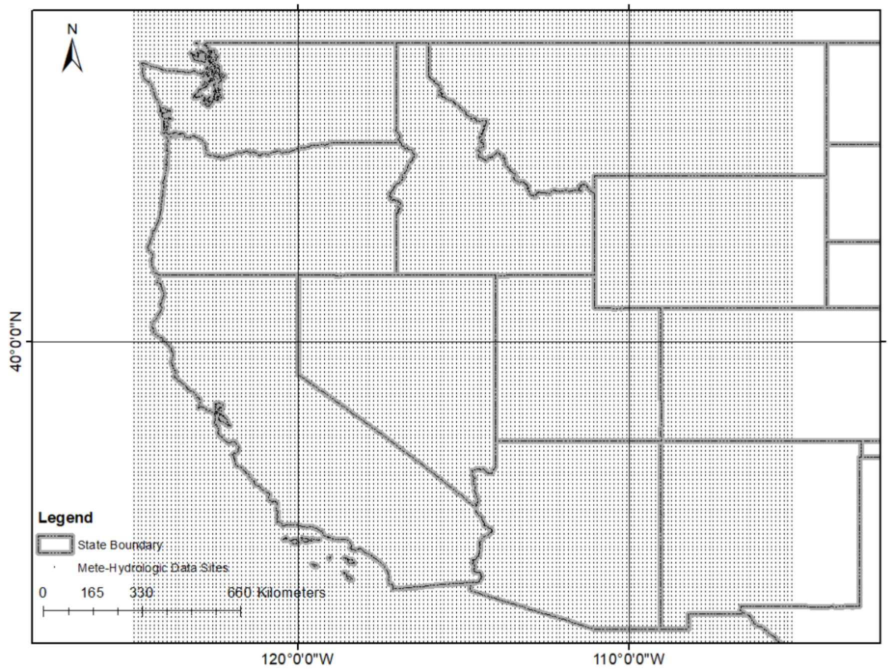


Figure 2 Meteorological Data Gathering Sites in Western USA

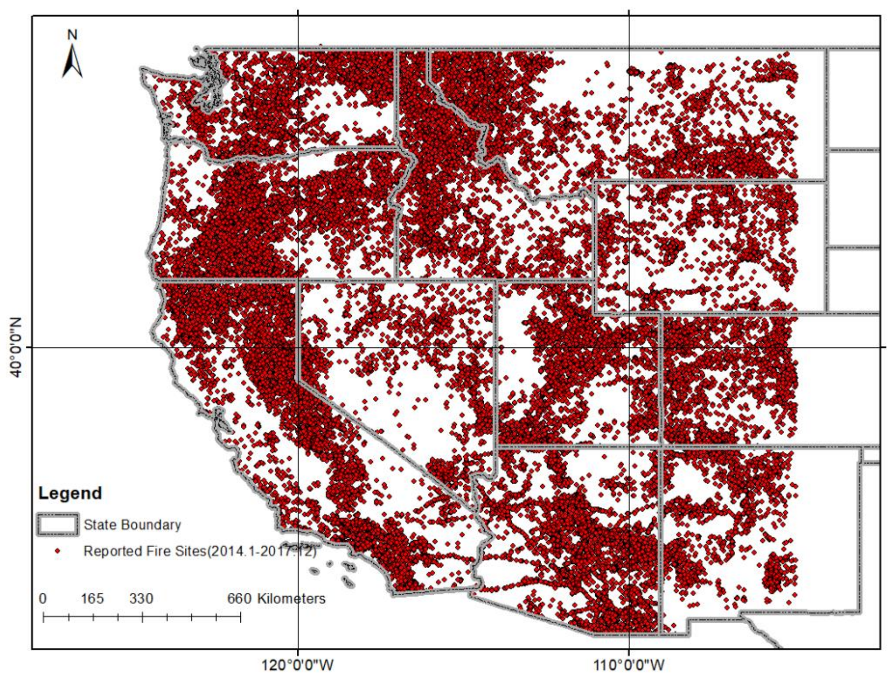


Figure 3 Reported Wildfire Sites during 2014 to 2017

3. Data analysis

(1) Data processing

a) Determining the geological information about calculation cells

Based on the resolution of meteorological data and the sites where the wildfires happen, the calculation cells have been confirmed (Figure 4). There are totally 11,011 grids where wildfire events occurred during the research period. All grids contain geological information (latitude and longitude). In order to calculate exactly, all grids have been ordered sequentially (the principle of name order has been presented in Figure 5), and the calculation has been finished via matlab based on the order of the grids. The start point located at the left bottom (Figure 5), and then the number of the grid has been ordered horizontally firstly, and row by row from bottom to top.

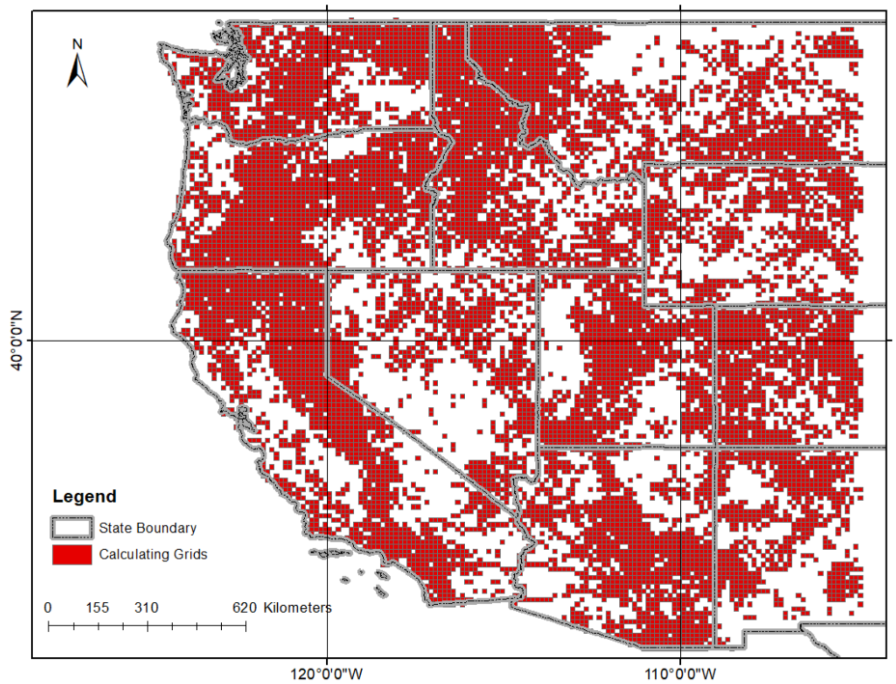


Figure 4 Calculation Cells in Western USA

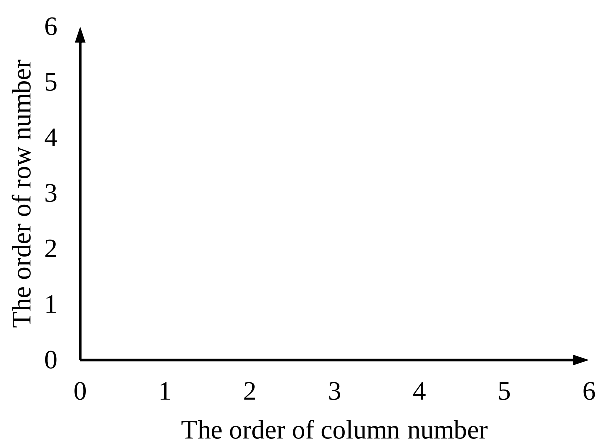


Figure 5 The Principle of Name order for 11011 Grids in Research Area

b) Determining the relationship among PET, P and wildfire activities (2014 to 2016)

By plotting the distribution of P and PET in the same graph (Figure 6), it can be seen that wildfire events (red circles) concentrated on the situation when P is low and PET is around 250mm, and the distribution of red circles accord with the normal distribution. Blue circles present that there are no wildfire events under that situation. To get the relationship among those three parameters (PET, P and wildfire risk), the normal distribution for P and PET has been calculated through matlab respectively, and the normal distribution has been showed in Figure 7. Equation 1 presents the normal distribution for PET, and Equation 2 for P.

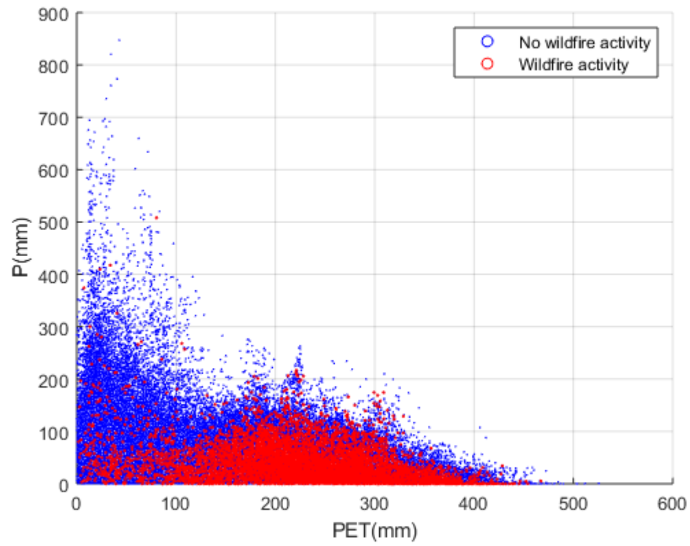
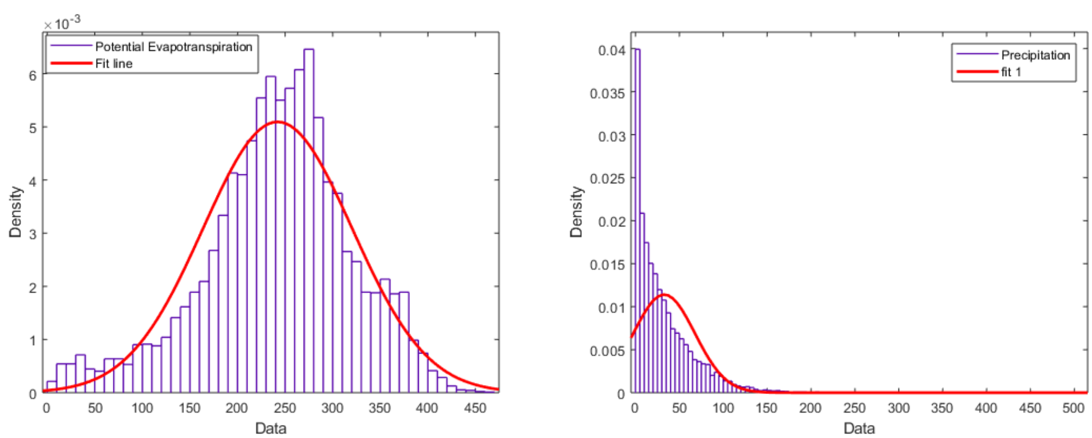


Figure 6 The Distribution of P and PET during 2014 to 2016



(a) **(b)**

Figure 7 Normal Distribution for PET and P

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi} \times 78.3192} e^{\frac{-(x-242.1116)^2}{2\times 78.3192^2}} \quad \text{Equation 1}$$

$$f(x;\mu,\sigma) = \frac{1}{\sqrt{2\pi} \times 34.9833} e^{\frac{-(x-32.6577)^2}{2\times 34.9833^2}} \quad \text{Equation 2}$$

Figure 7 and equations above illustrate the situation that around 68.2% wildfire events during 2014 to 2016 occurred when PET ranges from 163.8 mm to 320.4 mm and P ranges from 0 to 67.7 mm. Based on another property of normal distribution (Figure 8) – area equals to 1 – and the normal distribution for PET and P (Equation 1 and Equation 2), wildfire risk has been graded into 6 levels (Table 1). When both PET and P fall into the range $[-\sigma, \sigma]$, the wildfire risk (46.5124%) is the highest among other situations; when both PET and P fall into the range $[-\infty, -2\sigma]$ U $[2\sigma, +\infty]$, the wildfire risk (0.2116%) is the lowest. Similarly, other wildfire risks are explained by Table 1.

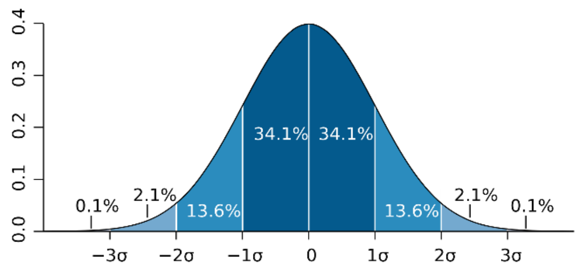


Figure 8 The Property of Normal Distribution

Table 1 Grading Wildfire based on the Normal Distribution of PET and P

Grades	Wildfire risk	The range for PET	The range for P
1	46.5124%	$[-\sigma, \sigma]$	$[-\sigma, \sigma]$
2	37.1008%	$[-\sigma, \sigma]$ or $[-2\sigma, -\sigma)$ U $(\sigma, 2\sigma]$	$[-2\sigma, \sigma)$ U $(\sigma, 2\sigma]$ or $[-\sigma, \sigma]$
3	7.3984%	$[-2\sigma, -\sigma)$ U $(\sigma, 2\sigma]$	$[-2\sigma, -\sigma)$ U $(\sigma, 2\sigma]$
4	6.2744%	$[-\sigma, \sigma]$ or $(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$	$(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$ or $[-\sigma, \sigma]$
5	2.5024%	$[-2\sigma, -\sigma)$ U $(\sigma, 2\sigma]$ *or* $(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$	$(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$ *or* $[-2\sigma, -\sigma)$ U $(\sigma, 2\sigma]$
6	0.2116%	$(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$	$(-\infty, -2\sigma)$ U $(2\sigma, +\infty)$

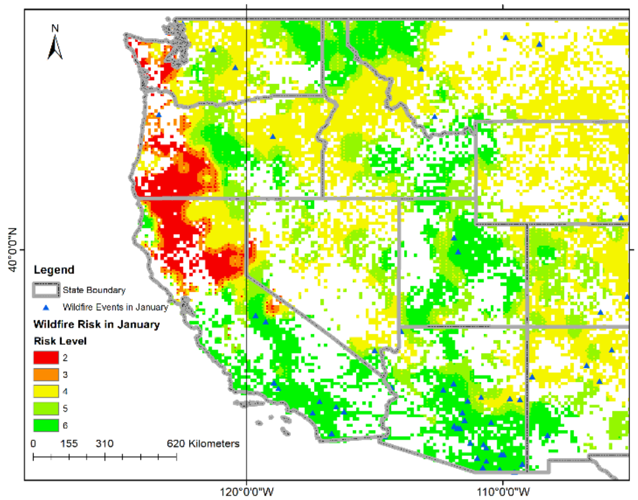
(2) Wildfire-risk prediction

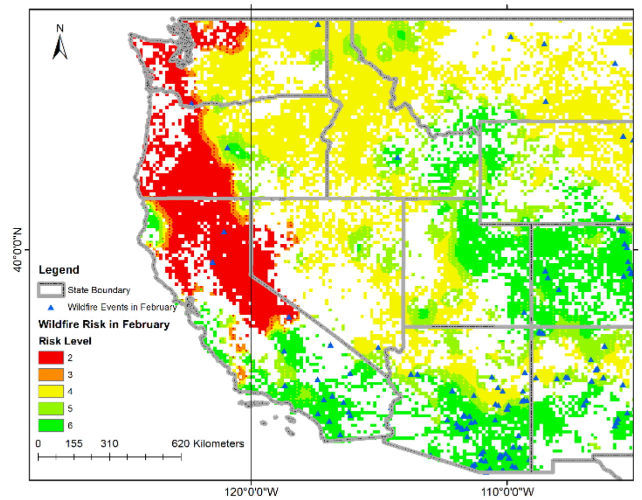
To verify whether the relationship between PET and P can be used to predict the wildfire risk, PET and P data from 2017 have been used to predict the wildfire risk based on the grades (Table 1). Figure 9 shows the results of the prediction for 2017. Different colors in the map present different wildfire-risk level (1 means the highest risk level), and the blue triangle means wildfire events occurred in 2017. Table 2 is the area for each risk level in western USA, which has been calculated based on the map in Figure 9.

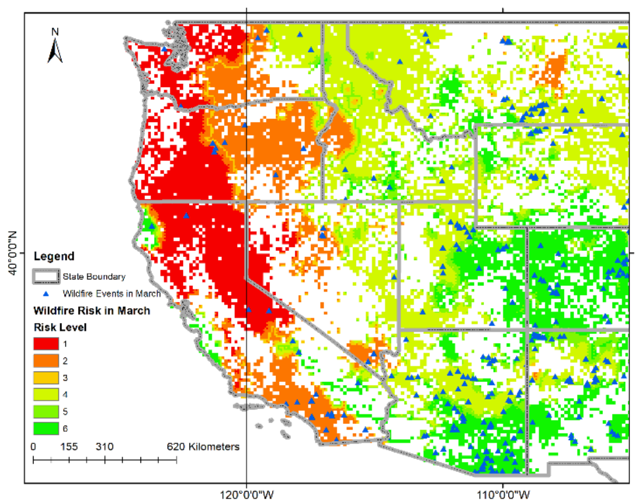
Table 2 The Area for Each Wildfire Risk Level in Each Month (km^2)

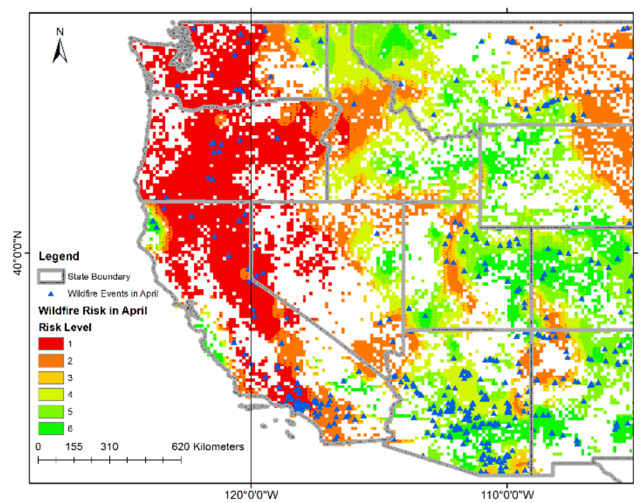
Risk Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0	0	84928	143045	286818	316583	294613	373844	303521	113965	1199	1670
2	42314	78632	81887	115892	130967	118462	113151	68910	140390	256453	155593	89039
3	128	0	0	0	0	86	2527	0	0	43	0	0
4	240906	233497	181547	98204	21757	11735	35804	4154	2998	58460	185016	301936
5	72036	48395	36532	59745	6424	43	814	0	0	12591	47582	28224
6	94435	89296	64927	32935	3855	2912	2912	2912	2912	8309	60430	28952

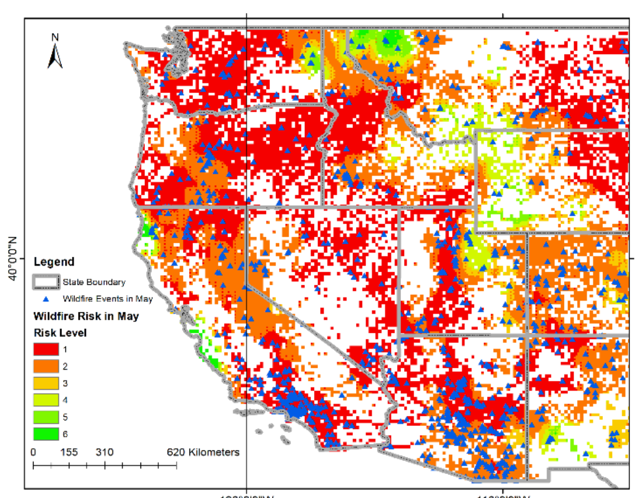
The spatial distribution of wildfire-risk levels obviously varies month by month. Based on the prediction of wildfire risk, wildfire-risk-level 1 is active during May to September and inactive in January, February, November and December. There should be a strong relationship, which should be applicable for each month: wildfire events concentrate on red area (risk level 1) and the number of wildfire events should be the smallest in green area (risk level 6). However, wildfire events are mainly located in red area during May to September. Wildfire events occurred in other places where they have been marked as low risk levels in other months. For example, most wildfire events occurred in red area during May to September; occurred in south-west of USA where they have been marked as risk level 6 in January.

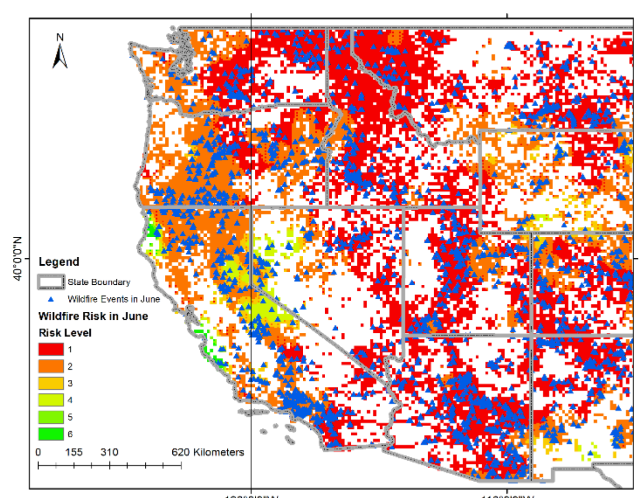












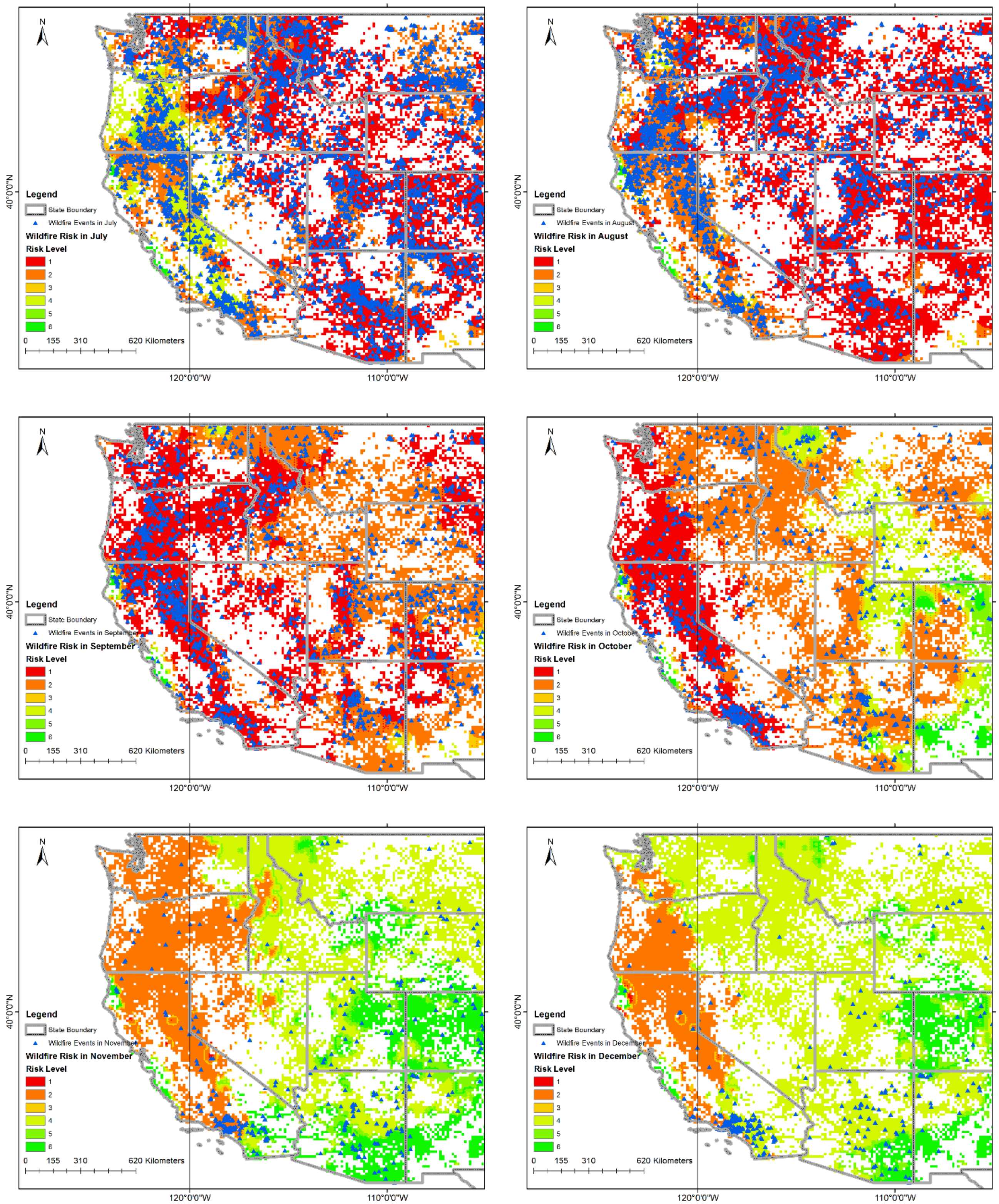


Figure 9 Monthly Spatial Distribution of the Wildfire-risk Level in Western USA (January 2017 to December 2017)

Table 3 not only shows the differential between prediction and reality but also illustrates the temporal change in 2017. Firstly, the figures in Table 3 can be seen as what levels the prediction defined for the wildfire events in 2017. For example, in January, 9.4% and 53.6% wildfire events have been defined as risk level 2 and risk level 4 respectively. Secondly, if the percentage in risk level 1 means the success rate for prediction, the wildfire activities can be predicted successfully during May to September: more than 60% of wildfire events have been predicted. August is the month that wildfire activities can be predicted precisely (83.1%). The wildfire activities occurred in January, February, November and December cannot be predicted effectively since the percentage in risk level 1 is 0.0%, 0.0% 0.3% and 0.4% respectively. In these four months, around 50% wildfire events have been defined in risk level 4 (only November is 41.1%). In March, April and October, 18.9% to 25.3% wildfire events can be predicted. 40.4% of wildfire events occurred in March have been defined in risk level 4, 57.0% in October in risk level 2, and 67.1% in December in risk level 4.

Table 3 The Distribution of Wildfire Risk Level in Each Month (%)

Risk Level	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	0.0	0.0	18.9	31.8	63.8	70.4	65.5	83.1	67.5	25.3	0.3	0.4
2	9.4	17.5	18.2	25.8	29.1	26.3	25.2	15.3	31.2	57.0	34.6	19.8
3	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0
4	53.6	51.9	40.4	21.8	4.8	2.6	8.0	0.9	0.7	13.0	41.1	67.1
5	16.0	10.8	8.1	13.3	1.4	0.0	0.2	0.0	0.0	2.8	10.6	6.3
6	21.0	19.9	14.4	7.3	0.9	0.6	0.6	0.6	0.6	1.8	13.4	6.4

4. Discussion

Many processes in this project deserve a deep discussion. During the processing of the original data, PET in some grids is smaller than 0 (negative value). PET is the amount of evaporation that occurred when sufficient water sources were available. It should be bigger than 0 even when the temperature is smaller than 0. Thus, the grid in which the PET is smaller than 0 has been deleted artificially.

Many wildfire events in 2017 occurred in the area in which has been identified as the low risk for wildfire activities, especially outside the period from May to September. Whether the relationship among those three parameters cannot be used in this period can hardly be identified since human activities have been identified as the main reason for wildfire events (Andrews, Finney, and Fischetti 2007) even in the situation which is not that suitable for wildfire activities. For example, mineral water bottles, which have been left in grassland, park or forest, can lead a high temperature for local area, and it may result in a wildfire.

In addition, the quality of raw data should be tested with other data, and the research period can be extended for more than 10 years. In general, the conclusion in this project deserve people to pay much more attention to the possibility of wildfire activities, especially in middle period of one year.

5. Conclusion

Based on the current monthly meteorological and wildfire data between 2014 and 2017, the relationship among PET, P and wildfire risk has been explored firstly. By comparing the value of PET and P in both wildfire period and safe period (no wildfire) during 2014 to 2016, the normal distributions for bot PET and P have been found, and 6 risk levels have been set. As the data for 2017 has been provided, the relationship received from the data during 2014 to 2016 has been verified. The results received from this project have been list below:

1) By predicting, wildfire risk mainly concentrates on the period from May to September.

2) More than 60% of wildfire events can be predicted successfully during the period from May to September when “risk level 1” has been viewed as the signal to judge whether the prediction is effective. However, the wildfire events in January, February, March, November and December cannot be predicted successfully based on the same principle.
3) In January, February, March, November and December, most wildfire events occurred in 2017 have been identified in the area where they have been identified as “risk level 4”, but October has been identified as “risk level 2”.

Reference:

Andrews, Patricia, Mark Finney, and Mark Fischetti. 2007. “Predicting Wildfires.” *Scientific American* 297 (2): 46–55. https://doi.org/10.1038/scientificamerican0807-46.

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Westerling, A. L., A. Gershunov, T. J. Brown, D. R. Cayan, and M. D. Dettinger. 2003. “Climate and Wildfire in the Western United States.” *Bulletin of the American Meteorological Society* 84 (5): 595–604. https://doi.org/10.1175/BAMS-84-5-595.

Appendix

(1) Matlab code for creating database based on the geological information of research grids.

```
clc;
clear;
close all;
cd 'F:\Courses\1st Semester\GIS\Project\Dataprocess'
excel = xlsread('GridsInfo.xlsx'); %this file is an output file from ArcGIS Pro (or
ArcMap), which contains geological information about the research area
%%  % Sort based on Rows (for sure to read the data accurately)
[~,idx] = (sort(excel(:,4)));
excel = excel(idx,:);
Rows=excel(:,4);
Row_test=unique(Rows);
for i=1:numel(Row_test)
Size_Rows(i)=sum(Rows(:) == Row_test(i));
end
nn=1;
mm=0;
for K=1:numel(Size_Rows)
mm=mm+(Size_Rows(K));
Small_Excel= excel([nn:mm],:);
[~,idx] = sort(Small_Excel(:,5));
excel02 = Small_Excel(idx,:);
excel_Soretd([nn:mm],:)=excel02;
excel02=[];
idx=[];
Small_Excel=[];
nn=mm+1;
end
dlmwrite('Newexcel.txt',excel_Soretd);
%%   read data from NC files based on the geological information
%1 Precipitation
```

```
Matrix_P = nan(48,11011);
for ip = 1:48 %length of month
   filename = ['PPET',num2str(ip),'.nc'] ;
   P_read = ncread(filename,'APCP');
   [b] = pcolor(P_read); colorbar; set(b,'edgecolor','none');
   PcolID = excel_Soretd(:,5);
   ProwID = excel_Soretd(:,4);
   cell_mon = nan(1,11011);
   for icell = 1:length(PcolID)
        celltmp = P_read(PcolID(icell),ProwID(icell));
        cell_mon(:,icell) = celltmp;
   end
   Matrix_P(ip,:) = cell_mon;
end
% 2 Potential Evapotranspiration
Matrix_PET = nan(48,11011);
for ip = 1:48 %length of month
   filename = ['PPET',num2str(ip),'.nc'] ;
   PET_read = ncread(filename,'PEVAP');
   PETcell_mon = nan(1,11011);
   for icell = 1:length(PcolID)
       PETcelltmp = PET_read(PcolID(icell),ProwID(icell));
       PETcell_mon(:,icell) = PETcelltmp;
   end
   Matrix_PET(ip,:) = PETcell_mon;
end
save('Calculation_data.mat','Matrix_PET','Matrix_P');
```

(2) Matlab code for calculating the relationship between PET and P in grids where they occurred wildfire activity. (2014 to 2016)

```
%% 2014-2016
%scatter diagram
% to get the data for the month where it occurred wildfires
fire_P_pre = nan(10503,1);
fire_PET_pre = nan(10503,1);
P_pre = Matrix_P(1:36,:);
PET_pre = Matrix_PET(1:36,:);
excel_pre = excel(1:9478,:);
 for ifire_pre = 1:9478
    fire_ptmp_pre = P_pre(excel_pre(ifire_pre,4),ifire_pre);
    fire_pettmp_pre = PET_pre(excel_pre(ifire_pre,4),ifire_pre);
    fire_P_pre(ifire_pre,:) = fire_ptmp_pre;
    fire_PET_pre(ifire_pre,:) = fire_pettmp_pre;
 end
P_pre_re = reshape(P_pre,36*10503,1);
PET_pre_re = reshape(PET_pre,36*10503,1);

figure(2)
scatter(P_pre_re,PET_pre_re,0.5,'b');
xlabel P(mm)
ylabel PET(mm)
hold on
scatter(fire_P_pre,fire_PET_pre,2,'r');
grid on;
title ('From 2014 to 2016');
%% plot the distribution
figure(3)
scatter(fire_P_pre,fire_PET_pre,2,'r');
xlabel P(mm)
ylabel PET(mm)
grid on;
title ('Wildfire during 2014 to 2016');
```

(3) Matlab code for predicting wildfire activities in 2017.

```
%% predicting the wildfire activities based on the 6 risk levels
% to get the data for the month where it occurred wildfires
Matrix_PET_17 = Matrix_PET(37:end,:);
Matrix_P_17 = Matrix_P(37:end,:);
% reshape both, and the results can be used for mapping
Reshape_PET_17 = reshape(Matrix_PET_17,126036,1);
Reshape_P_17 = reshape(Matrix_P_17,126036,1);
% grade each of them
G_R = [Reshape_PET_17,Reshape_P_17];
grade = nan(126036,1);
for igrade = 1:126036
    if (G_R(igrade,1)>=163.7924 && G_R(igrade,1)<=320.4308) && (G_R(igrade,2)>=0 &&
G_R(igrade,2)<=67.641)
        tmp_gra = 1;
    elseif (G_R(igrade,1)>=163.7924 && G_R(igrade,1)<=320.4308 && (G_R(igrade,2)>67.641 &&
G_R(igrade,2)<=102.6243)) || ((G_R(igrade,1)>=85.4732 && G_R(igrade,1)<163.7924) ||
(G_R(igrade,1)>320.4308 && G_R(igrade,1)<=398.75) && G_R(igrade,2)<=67.641)
        tmp_gra = 2;
    elseif (G_R(igrade,1)>=85.3676 && G_R(igrade,1)<163.7924 || G_R(igrade,1)<=398.75 &&
G_R(igrade,1)>320.4308) && (G_R(igrade,2)<=102.6243 && G_R(igrade,2)>67.641)
        tmp_gra = 3;
    elseif ((G_R(igrade,1)>=163.7924 && G_R(igrade,1)<=320.4308) && G_R(igrade,2)>102.6243)
|| ((G_R(igrade,1)<85.4732 || G_R(igrade,1)>398.75) && G_R(igrade,2)<67.641)
        tmp_gra = 4;
    elseif ((G_R(igrade,1)>=85.3676 && G_R(igrade,1)<163.7924) || (G_R(igrade,1)<=398.75 &&
G_R(igrade,1)>320.4308) && G_R(igrade,2)>102.6243) || (((G_R(igrade,1)<85.4732 ||
G_R(igrade,1)>398.75)) && (G_R(igrade,2)<=102.6243 && G_R(igrade,2)>67.641))
        tmp_gra = 5;
    else tmp_gra = 6;
    end
    grade(igrade,:) = tmp_gra;
end
% reshape to the original version
Grade_reshape = reshape(grade,12,10503);
% to find the coordinates (the row number which contains unqualified data should be
deleted)
excel(Index',:)=[];
co_lat = excel(:,7);
co_lon = excel(:,8);
Wildfire_risk_17 = [co_lat,co_lon,Grade_reshape'];
```