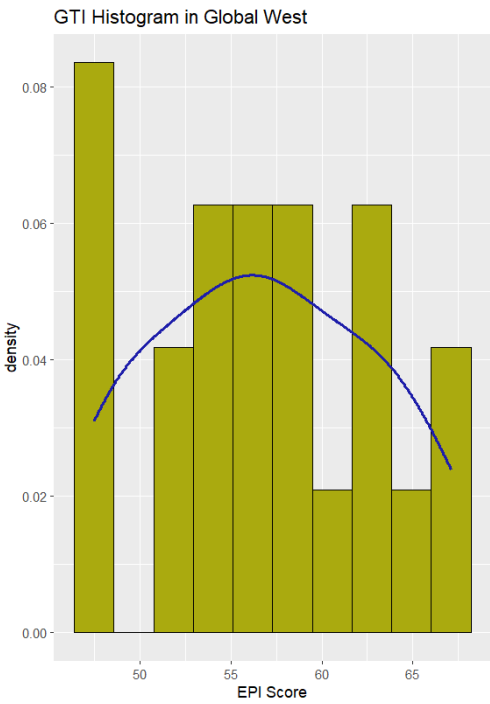
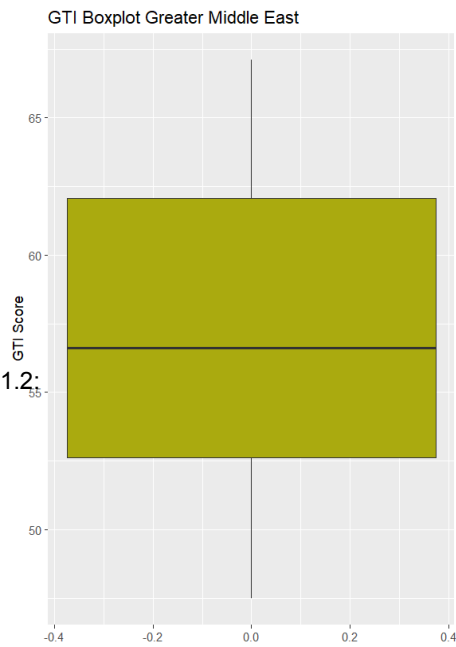
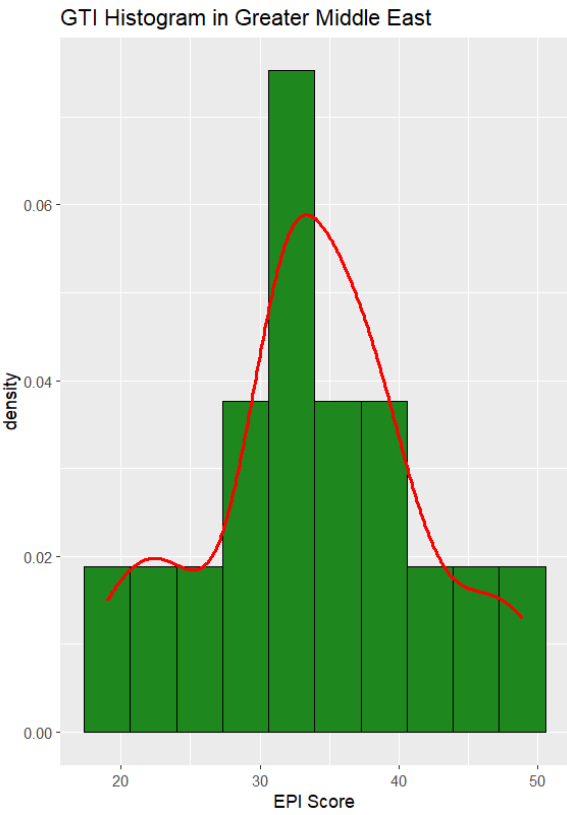
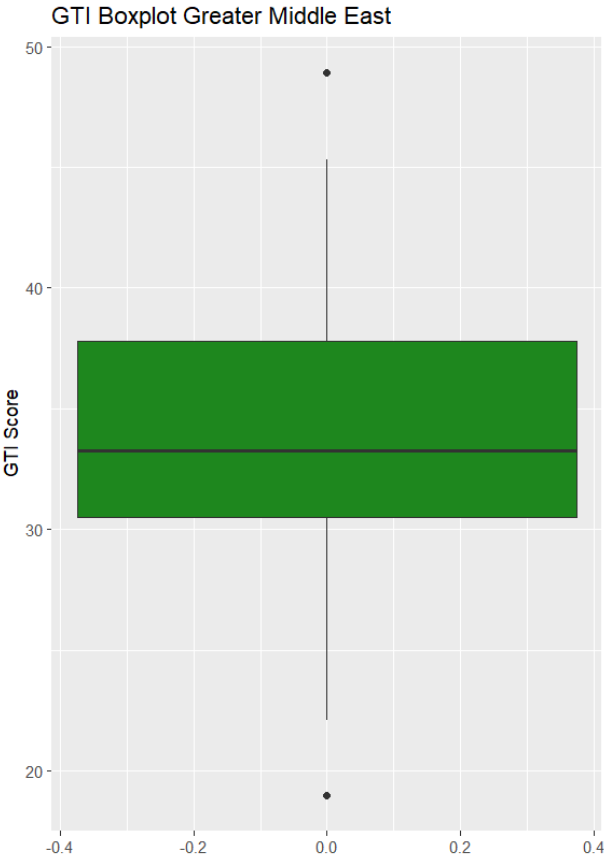
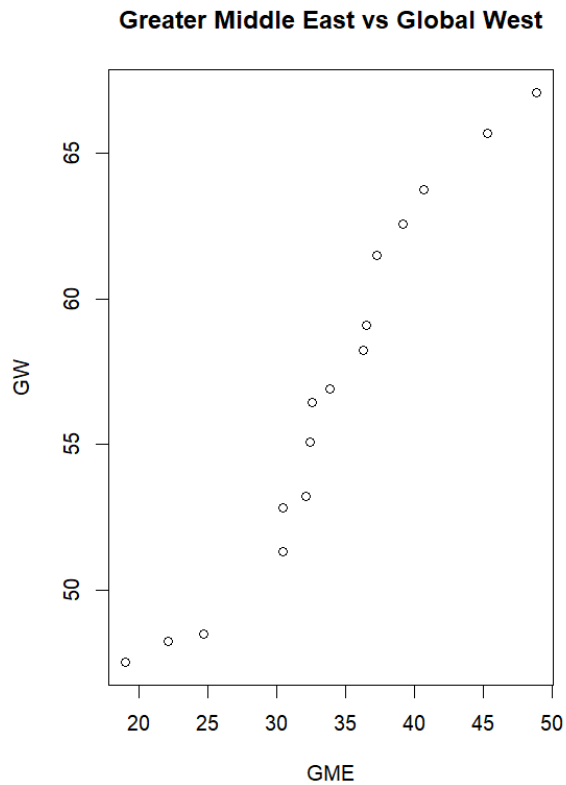


Variable Distributions:

1)

1.1:





2)

2.1:

GTI vs GDP Model

Call:

lm(formula = GTI.new ~ gdp, data = Data)

Residuals:

Min	1Q	Median	3Q	Max
-36.204	-5.547	1.632	7.911	35.694

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.129e+01	1.312e+00	23.851	< 2e-16 ***
gdp	2.399e-04	3.064e-05	7.827	4.39e-13 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 12.42 on 177 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.2571, Adjusted R-squared: 0.2529

F-statistic: 61.26 on 1 and 177 DF, p-value: 4.389e-13

GTI vs Population Model

Call:

lm(formula = GTI.new ~ population, data = Data)

Residuals:

Min	1Q	Median	3Q	Max
-38.841	-8.373	0.742	9.209	40.050

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	3.886e+01	1.125e+00	34.544	<2e-16 ***
population	-4.287e-09	6.941e-09	-0.618	0.538

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

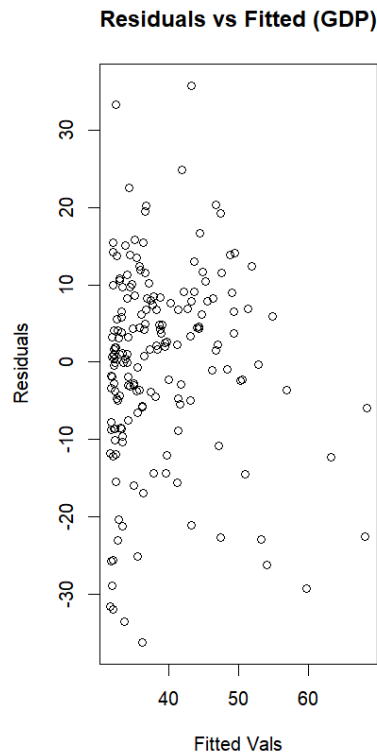
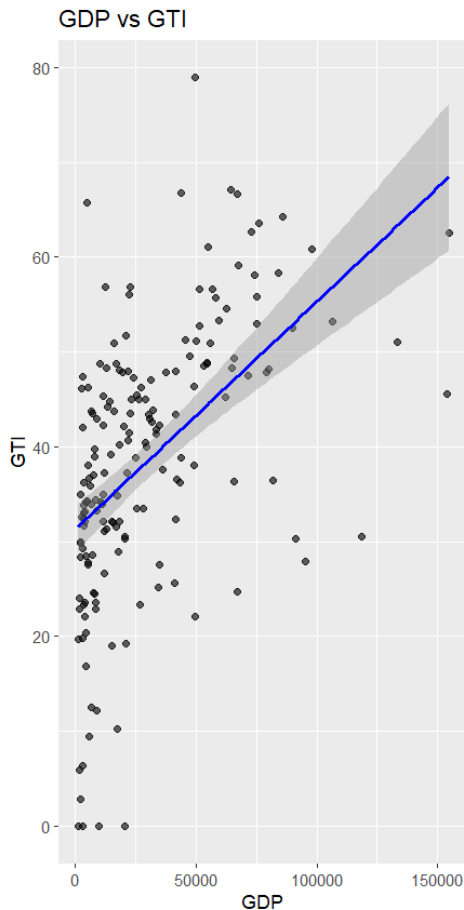
Residual standard error: 14.47 on 177 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.00215, Adjusted R-squared: -0.003488

F-statistic: 0.3814 on 1 and 177 DF, p-value: 0.5377

GDP is the better predictor



2.2:

GTI vs GDP (Log)

Call:

```
lm(formula = GTI.new ~ log(gdp), data = Data)
```

Residuals:

Min	1Q	Median	3Q	Max
-39.846	-6.131	1.394	6.678	36.333

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-30.7403	7.3042	-4.209	4.08e-05 ***
log(gdp)	7.1093	0.7442	9.553	< 2e-16 ***

Signif. codes:

0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 11.71 on 177 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.3402, Adjusted R-squared: 0.3365

F-statistic: 91.27 on 1 and 177 DF, p-value: < 2.2e-16

GTI vs Population (Log)

Call:

```
lm(formula = GTI.new ~ log(population), data = Data)
```

Residuals:

Min	1Q	Median	3Q	Max
-39.171	-8.186	0.890	8.878	39.187

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	48.0307	8.7514	5.488	1.39e-07 ***
log(population)	-0.5887	0.5460	-1.078	0.282

Signif. codes:

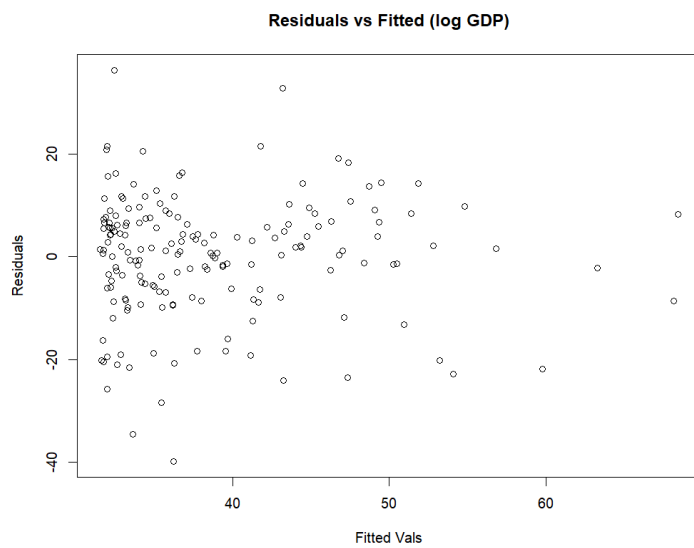
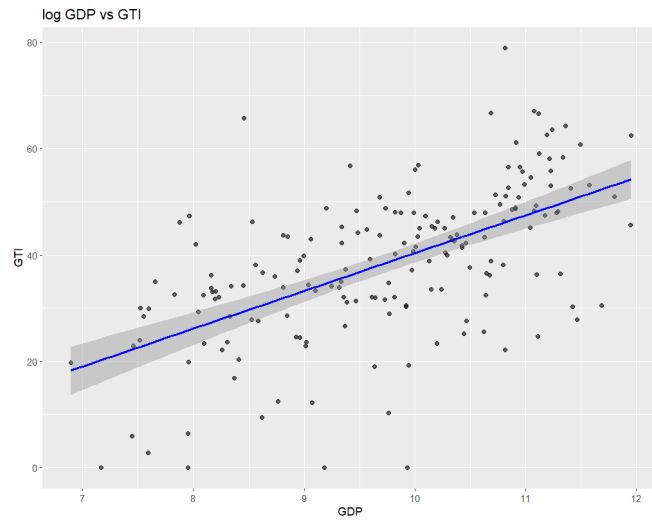
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 14.44 on 177 degrees of freedom

(1 observation deleted due to missingness)

Multiple R-squared: 0.006526, Adjusted R-squared: 0.0009136

F-statistic: 1.163 on 1 and 177 DF, p-value: 0.2824



The log transformation is better than the original model. This is because p remained highly significant while decreasing residual standard error.

3)

3.1:

k=5

Confusion Matrix:

Predicted	Actual			
	Asia-Pacific	Global West	Latin America & Caribbean	
Asia-Pacific	3	0	2	
Global West	0	0	0	
Latin America & Caribbean	5	2	12	
Southern Asia	0	0	0	
Sub-Saharan Africa	0	0	0	

Predicted	Actual	
	Southern Asia	Sub-Saharan Africa
Asia-Pacific	1	1
Global West	0	0
Latin America & Caribbean	0	0
Southern Asia	0	0
Sub-Saharan Africa	0	1

Accuracy:

```
> print(paste("Model 1 Accuracy:", round(accuracy, 4)))
[1] "Model 1 Accuracy: 0.5926"
```

3.2:

Confusion Matrix:

Predicted	Actual				
	Asia-Pacific	Global West	Latin America & Caribbean	Southern Asia	
Asia-Pacific	5	0	2	1	
Global West	0	1	0	0	
Latin America & Caribbean	3	1	12	0	
Southern Asia	0	0	0	0	
Sub-Saharan Africa	0	0	0	0	

Predicted	Actual	
	Sub-Saharan Africa	
Asia-Pacific	0	
Global West	0	
Latin America & Caribbean	1	
Southern Asia	0	
Sub-Saharan Africa	1	

Accuracy:

```
> print(paste("Model 2 Accuracy:", round(accuracy2, 4)))
[1] "Model 2 Accuracy: 0.7037"
```

Model 2 is a better model as it achieved ~70% accuracy whereas the first reached ~59%. Model 2 also was more correct across more regions.