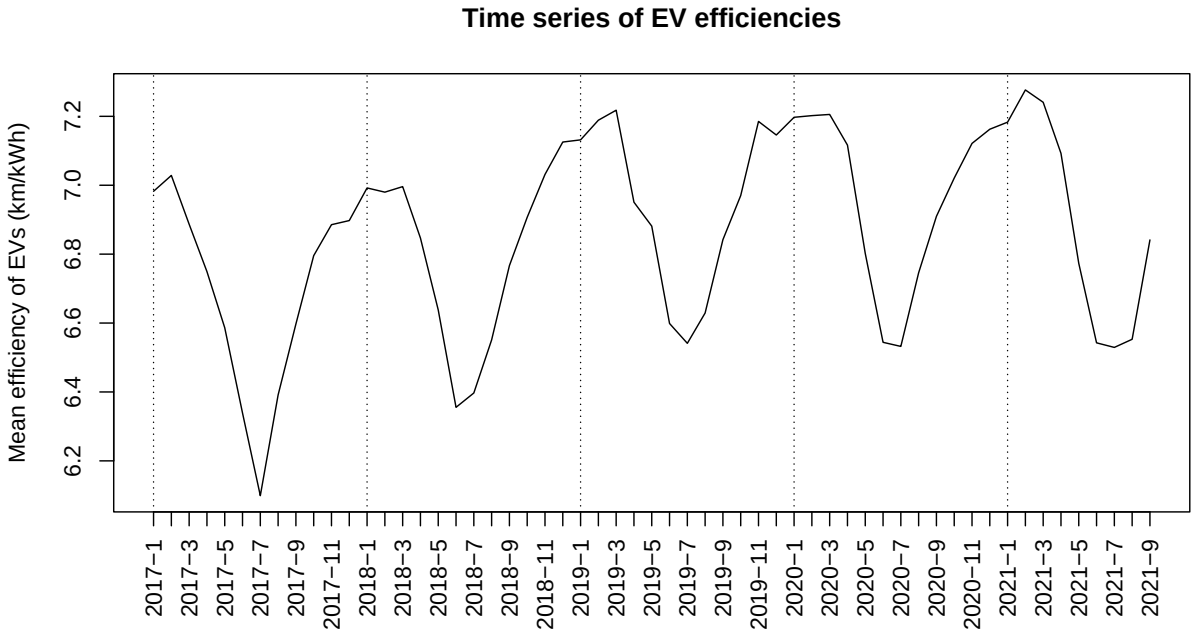
EV data findings

pablo paulsen

23/11/2021

```
## # A tibble: 25 x 3
## # Groups:   region [25]
##    region           weather_region count
##    <chr>            <fct>          <int>
##  1 Auckland         Auckland         330
##  2 Wellington       Upper Hutt       238
##  3 Christchurch     Christchurch     146
##  4 Coastal Otago    Dunedin          132
##  5 Waikato          Hamilton          65
##  6 Bay of Plenty    Rotorua           53
##  7 North Canterbury Christchurch      34
##  8 Central Otago    Clyde             31
##  9 Mid Canterbury   Christchurch      31
## 10 Nelson           Nelson            31
## # ... with 15 more rows
```

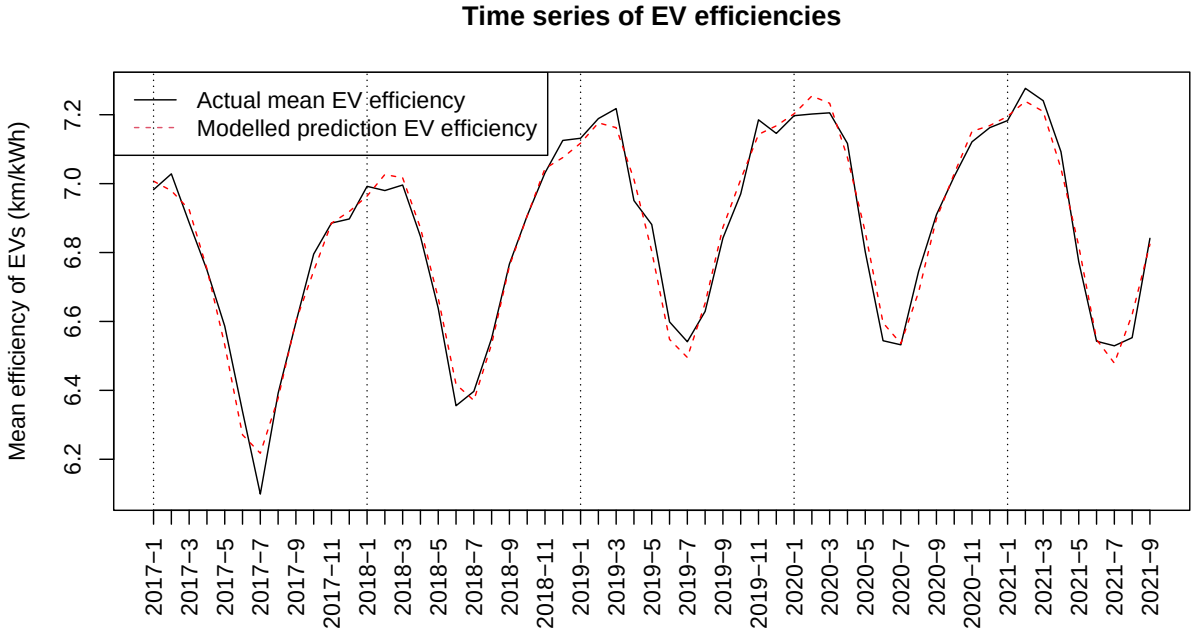
```
## # A tibble: 13 x 2
##    weather_region   count
##    <fct>            <int>
##  1 Auckland           386
##  2 Upper Hutt         249
##  3 Christchurch       226
##  4 Dunedin            139
##  5 Hamilton            65
##  6 Rotorua             53
##  7 Nelson              52
##  8 Clyde               31
##  9 Palmerston North    29
## 10 Stratford           20
## 11 Napier              17
## 12 Invercargill         9
## 13 <NA>                 4
```



simple linear model with mean_eff $= t + \ln t + t^2$+month (as factor). negative squared term means can not use for long term efficiency trend as it will got negative but allows it to better fit the seasonal trend

```
##
## Call:
## lm(formula = mean_ef ~ m + I(log(m)) + I(m^2) + factor(month),
##     data = monthly_EV_data)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.118463 -0.027742 -0.003732  0.037674  0.077820
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)      6.971e+00  3.686e-02 189.156  < 2e-16 ***
## m                3.612e-02  4.303e-03   8.394 1.59e-10 ***
## I(log(m))       -1.607e-01  3.253e-02  -4.941 1.29e-05 ***
## I(m^2)          -3.834e-04  4.952e-05  -7.743 1.28e-09 ***
## factor(month)2   4.870e-02  3.037e-02   1.604    0.116
## factor(month)3   2.504e-02  3.066e-02   0.817    0.419
## factor(month)4  -1.343e-01  3.089e-02  -4.346 8.61e-05 ***
## factor(month)5  -3.518e-01  3.108e-02 -11.321 2.43e-14 ***
## factor(month)6  -6.154e-01  3.123e-02 -19.709  < 2e-16 ***
## factor(month)7  -6.753e-01  3.135e-02 -21.539  < 2e-16 ***
## factor(month)8  -5.247e-01  3.147e-02 -16.675  < 2e-16 ***
## factor(month)9  -3.109e-01  3.157e-02  -9.847 1.78e-12 ***
## factor(month)10 -1.776e-01  3.299e-02  -5.384 3.04e-06 ***
## factor(month)11 -5.172e-02  3.299e-02  -1.568    0.124
## factor(month)12 -3.111e-02  3.299e-02  -0.943    0.351
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

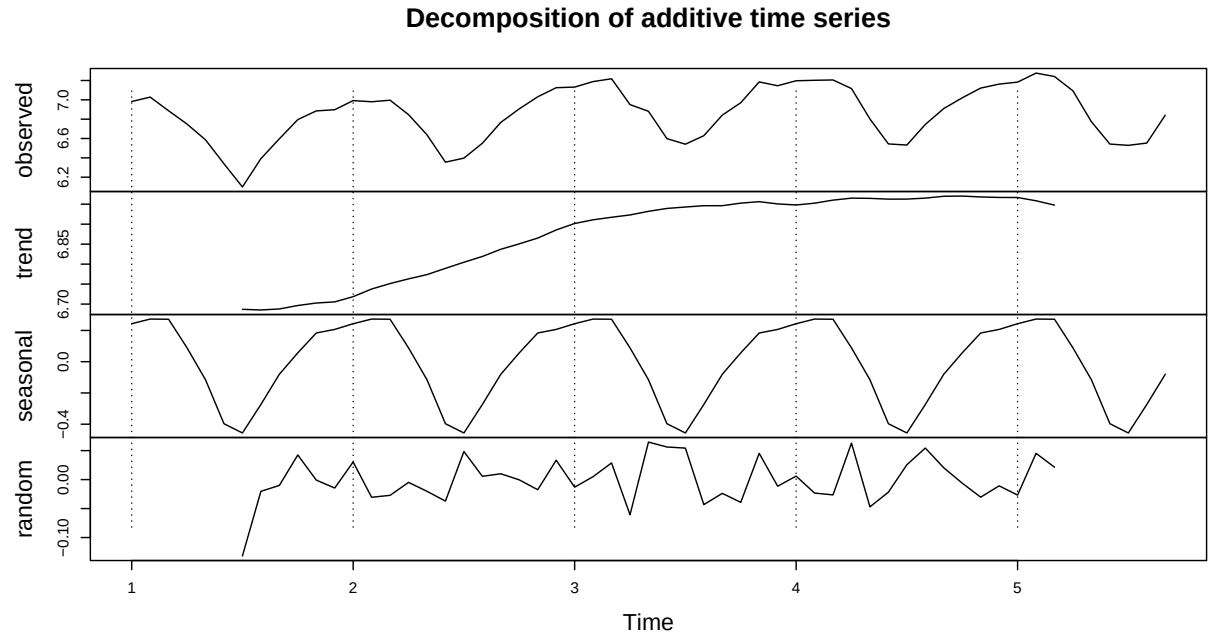
```
## Residual standard error: 0.04766 on 42 degrees of freedom
## Multiple R-squared:  0.9784, Adjusted R-squared:  0.9712
## F-statistic: 135.6 on 14 and 42 DF,  p-value: < 2.2e-16
```

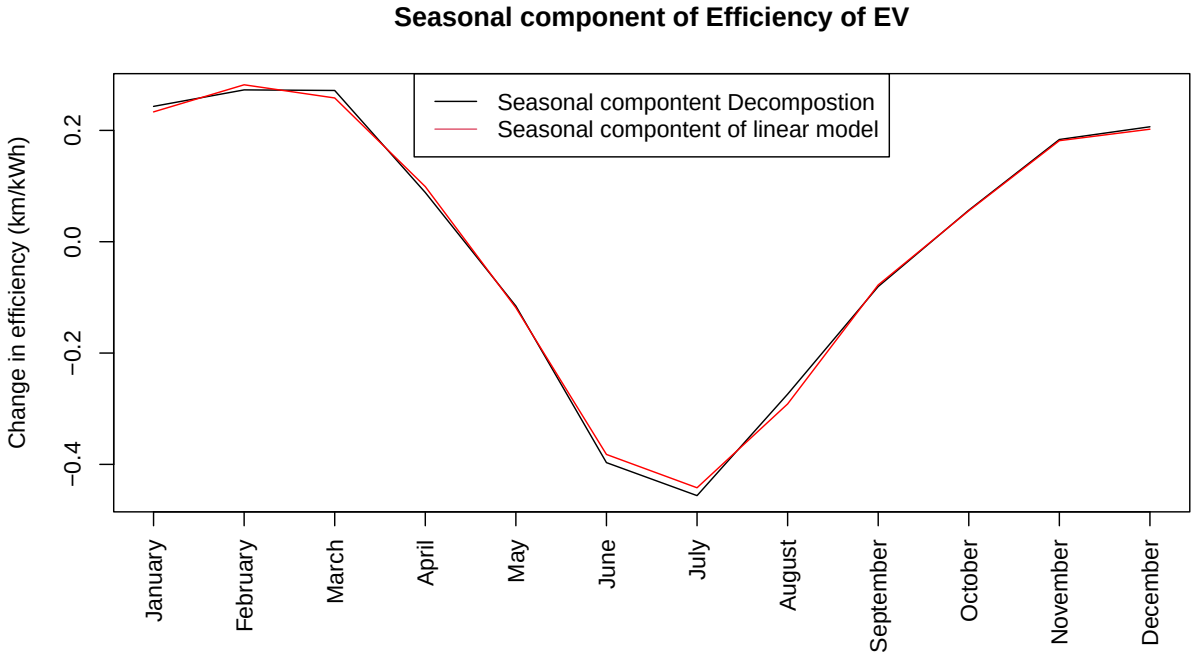



```
## Warning in adf.test(eff_series, alternative = "stationary"): p-value smaller
## than printed p-value
```

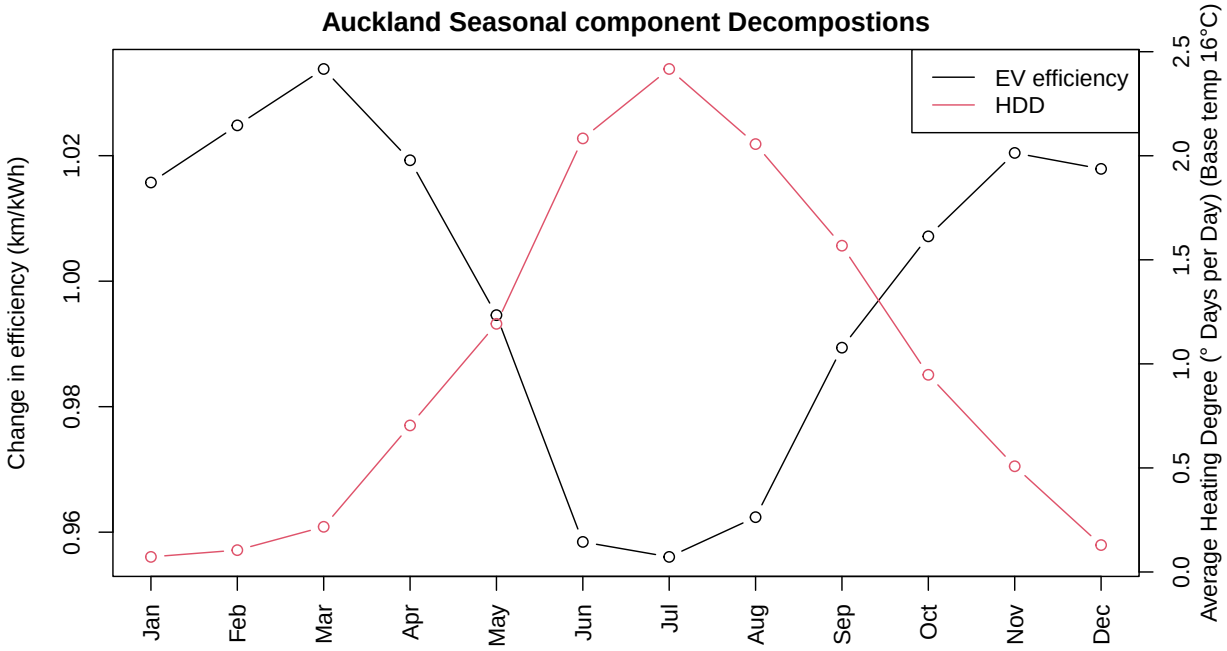
```
##
##  Augmented Dickey-Fuller Test
##
## data:  eff_series
## Dickey-Fuller = -4.7294, Lag order = 3, p-value = 0.01
## alternative hypothesis: stationary
```

we can reject null hypothesis that data is not-stationary. this makes sense as average efficiency should not have significantly changed in a couple of years. use multiplicative instead of additive as preferable to know estimated extra power use? or should i know total extra power used in season?





will only do for Auckland as too many lines would get crowded



intercept base line is Nissan Leaf (24 kWh) 2013-2016

```
##
## Call:
## lm(formula = efficiency ~ HDD + model, data = EV_data[year >=
##     2017, ], na.action = na.omit)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5432 -0.4944 -0.0231  0.4939  6.3735
##
## Coefficients:
##                                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)                              7.549555   0.010579 713.644  < 2e-16 ***
## HDD                                     -0.109873   0.001912 -57.474  < 2e-16 ***
## modelNissan Leaf (30 kWh)               -0.132918   0.013022 -10.207  < 2e-16 ***
## modelNissan Leaf (24 kWh) 2011-2012     -0.646832   0.015508 -41.709  < 2e-16 ***
## modelNissan Leaf (40 kWh)               -0.519153   0.027636 -18.786  < 2e-16 ***
## modelNissan e-NV200 (24 kWh)            -1.269486   0.024561 -51.688  < 2e-16 ***
## modelHyundai Ioniq (EV)                  0.890762   0.035024  25.433  < 2e-16 ***
## modelBMW i3                             -0.159919   0.041058  -3.895 9.85e-05 ***
## modelHyundai Kona (EV)                  -0.045573   0.048914  -0.932 0.351505
## modelRenault Zoe                        -0.453207   0.045542  -9.951  < 2e-16 ***
## modelTesla Model 3                      -0.586784   0.055693 -10.536  < 2e-16 ***
## modelNissan Leaf (62 kWh)               -1.029511   0.086268 -11.934  < 2e-16 ***
## modelKia Niro (EV)                      -0.480573   0.063210  -7.603 3.01e-14 ***
## modelTesla Model S                      -2.111177   0.079209 -26.653  < 2e-16 ***
## modelVolkswagen e-Golf                  -0.069197   0.069425  -0.997 0.318912
## modelConversion to EV                   -2.313183   0.097923 -23.622  < 2e-16 ***
## modelTesla Model-X                      -3.061412   0.085703 -35.721  < 2e-16 ***
## modelKia Soul                           -0.425754   0.071155  -5.983 2.22e-09 ***
## modelMG ZS EV                           -0.734845   0.198484  -3.702 0.000214 ***
```

```
## modelRenault Kangoo (van)           -2.155760   0.096331 -22.379  < 2e-16 ***
## modelJaguar I-PACE                  -2.518284   0.133950 -18.800  < 2e-16 ***
## modelAudi A3 e-tron                 -1.389717   0.271699  -5.115 3.16e-07 ***
## modelMitsubishi iMiev - car         -3.161913   0.543210  -5.821 5.94e-09 ***
## modelPeugeot e-208                  -0.346394   0.343668  -1.008 0.313498
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7681 on 22805 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.3354, Adjusted R-squared:  0.3347
## F-statistic: 500.4 on 23 and 22805 DF,  p-value: < 2.2e-16
```

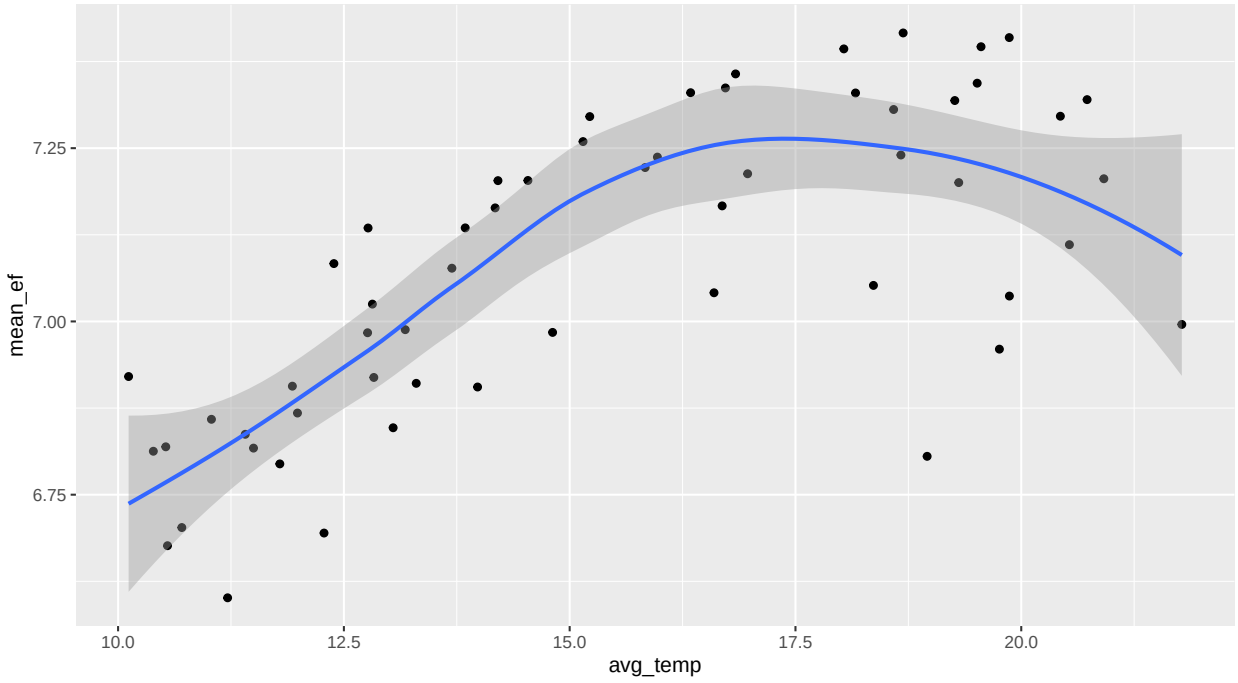
different city weather stations may be measuring colder or warmer regions of the city and therefore may need a slightly different scaling. interesting that Rotorua has lower effect on HDD, could be cause Rotorua is inland Bay of Plenty so its temperature change is more significant that coastal Tauranga which would also be included in bay of plenty.

```
##
## Call:
## lm(formula = efficiency ~ HDD + model, data = EV_data[year >=
##     2017, ], na.action = na.omit)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.5432 -0.4944 -0.0231  0.4939  6.3735
##
## Coefficients:
##                                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)                          7.549555   0.010579 713.644  < 2e-16 ***
## HDD                                 -0.109873   0.001912 -57.474  < 2e-16 ***
## modelNissan Leaf (30 kWh)           -0.132918   0.013022 -10.207  < 2e-16 ***
## modelNissan Leaf (24 kWh) 2011-2012 -0.646832   0.015508 -41.709  < 2e-16 ***
## modelNissan Leaf (40 kWh)           -0.519153   0.027636 -18.786  < 2e-16 ***
## modelNissan e-NV200 (24 kWh)        -1.269486   0.024561 -51.688  < 2e-16 ***
## modelHyundai Ioniq (EV)              0.890762   0.035024  25.433  < 2e-16 ***
## modelBMW i3                         -0.159919   0.041058  -3.895 9.85e-05 ***
## modelHyundai Kona (EV)              -0.045573   0.048914  -0.932 0.351505
## modelRenault Zoe                    -0.453207   0.045542  -9.951  < 2e-16 ***
## modelTesla Model 3                  -0.586784   0.055693 -10.536  < 2e-16 ***
## modelNissan Leaf (62 kWh)           -1.029511   0.086268 -11.934  < 2e-16 ***
## modelKia Niro (EV)                  -0.480573   0.063210  -7.603 3.01e-14 ***
## modelTesla Model S                  -2.111177   0.079209 -26.653  < 2e-16 ***
## modelVolkswagen e-Golf              -0.069197   0.069425  -0.997 0.318912
## modelConversion to EV               -2.313183   0.097923 -23.622  < 2e-16 ***
## modelTesla Model-X                  -3.061412   0.085703 -35.721  < 2e-16 ***
## modelKia Soul                       -0.425754   0.071155  -5.983 2.22e-09 ***
## modelMG ZS EV                       -0.734845   0.198484  -3.702 0.000214 ***
## modelRenault Kangoo (van)           -2.155760   0.096331 -22.379  < 2e-16 ***
## modelJaguar I-PACE                  -2.518284   0.133950 -18.800  < 2e-16 ***
## modelAudi A3 e-tron                 -1.389717   0.271699  -5.115 3.16e-07 ***
## modelMitsubishi iMiev - car         -3.161913   0.543210  -5.821 5.94e-09 ***
## modelPeugeot e-208                  -0.346394   0.343668  -1.008 0.313498
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.7681 on 22805 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.3354, Adjusted R-squared:  0.3347
## F-statistic: 500.4 on 23 and 22805 DF,  p-value: < 2.2e-16
```

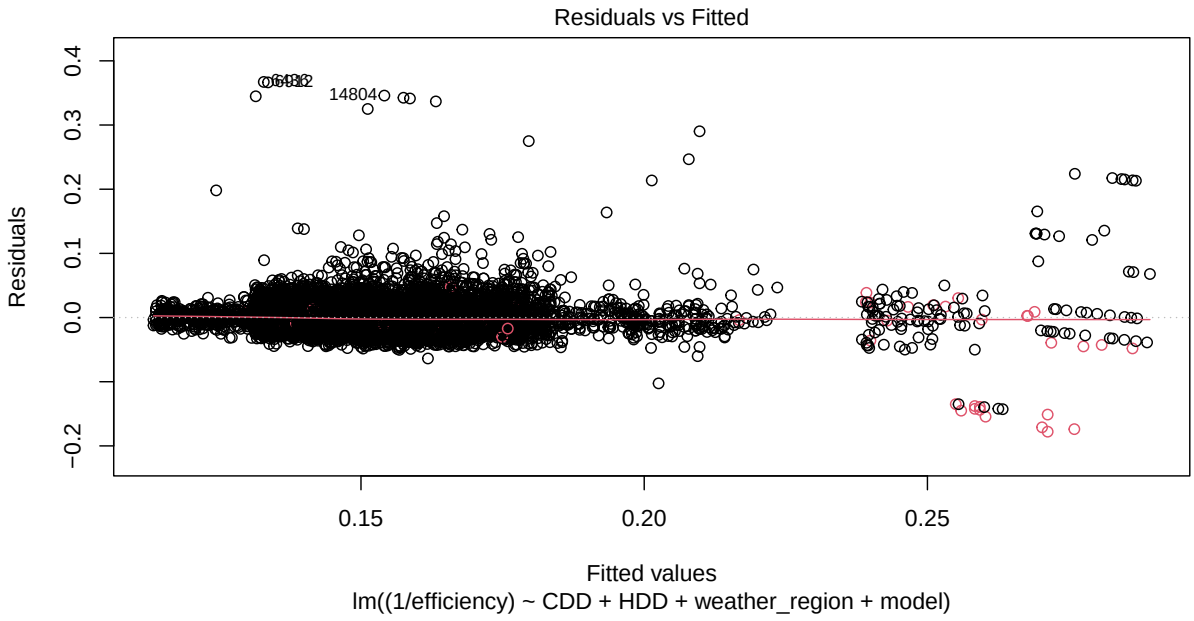
https://www.geotab.com/blog/ev-range/

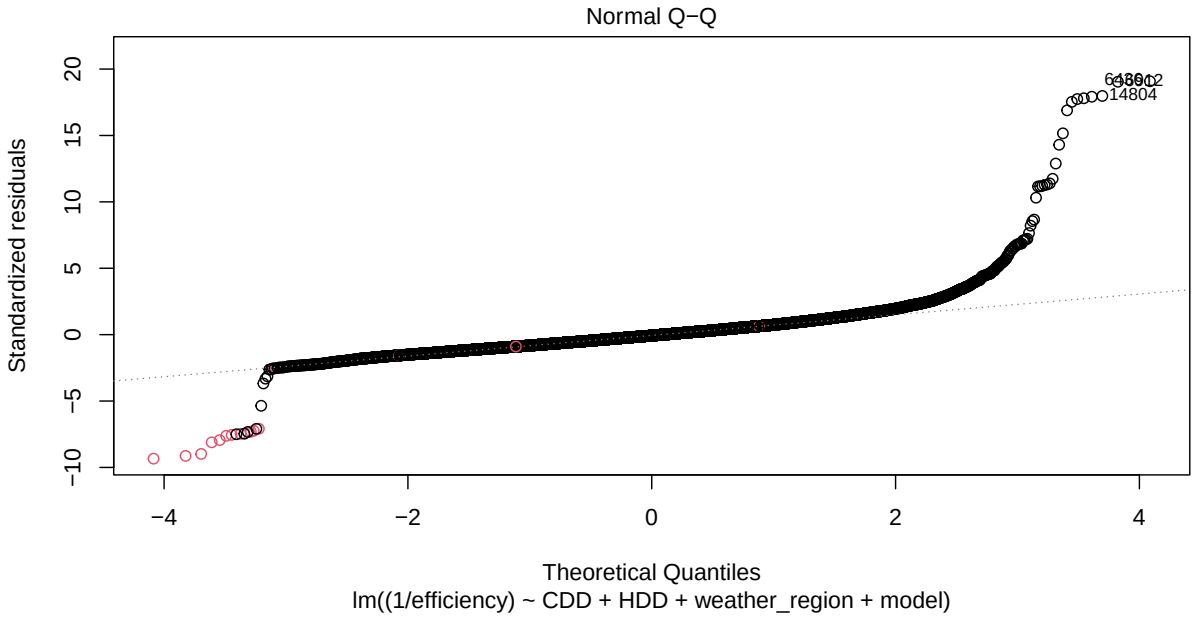
based on this AC should also decrease range. not too obvious in NZ as is kind of cold but in Auckland can see such a trend what if we include cooling degree days in analysis too? unlike this direct average temp vs efficiency plot this would allow for cooling and heating in the same month that could reduce efficiency. could explain the couple month that have very bad efficiency, possibley have a few cold and warm days but average is nothing unsual

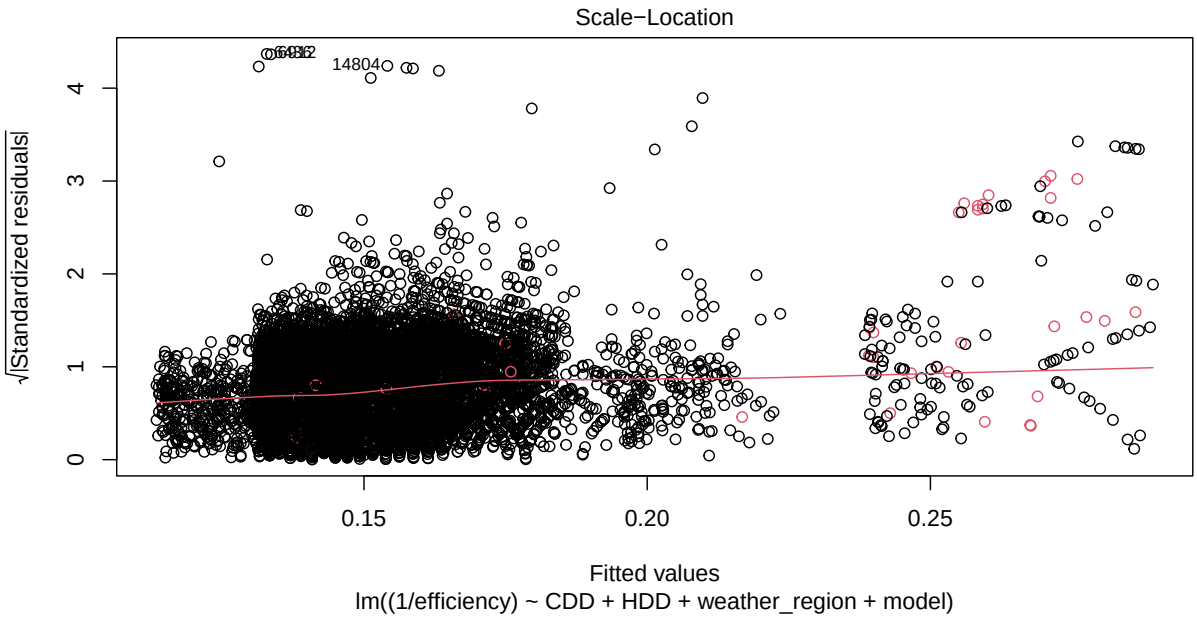


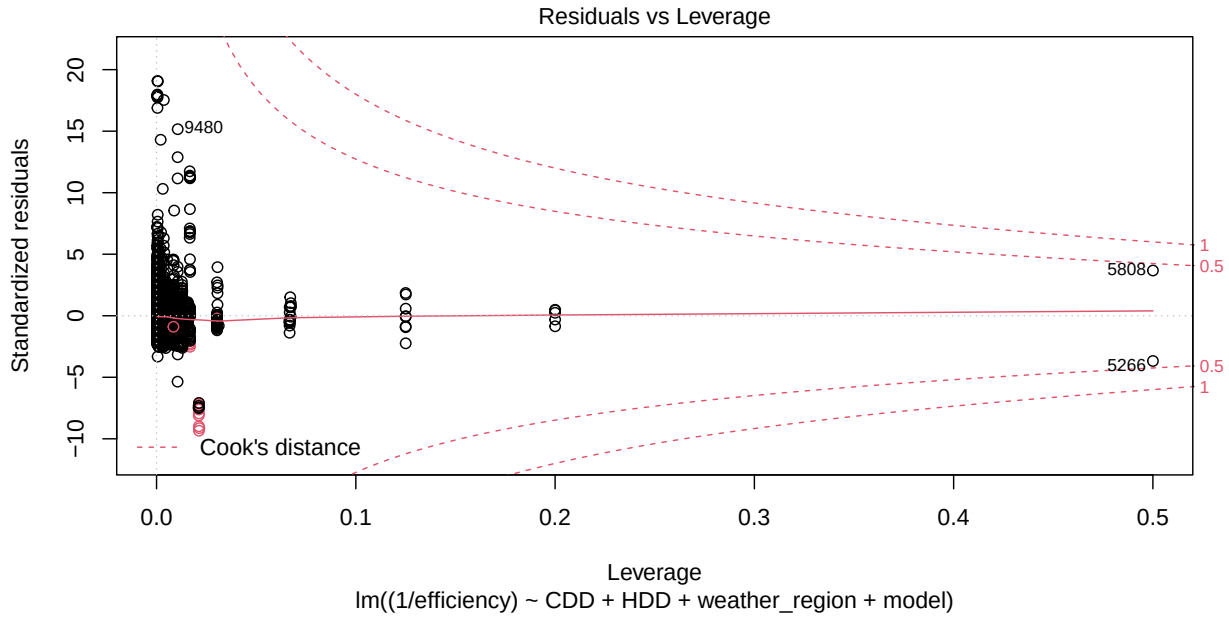

```
##
## Call:
## lm(formula = (1/efficiency) ~ CDD + HDD + weather_region + model,
##     data = EV_data[year >= 2017, ], na.action = na.omit)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.17786 -0.01118 -0.00136  0.00902  0.36716
##
## Coefficients:
##                                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       1.306e-01  3.623e-04 360.423  < 2e-16 ***
## CDD                               3.339e-03  7.486e-04   4.460 8.22e-06 ***
## HDD                               2.484e-03  6.535e-05  38.013  < 2e-16 ***
## weather_regionUpper Hutt          2.453e-05  3.916e-04   0.063 0.950059
## weather_regionChristchurch       -2.663e-03  4.130e-04  -6.449 1.14e-10 ***
## weather_regionDunedin             1.089e-02  4.725e-04  23.052  < 2e-16 ***
```

```
## weather_regionHamilton               6.488e-03  6.950e-04   9.335  < 2e-16 ***
## weather_regionRotorua                4.309e-04  7.055e-04   0.611 0.541327
## weather_regionNelson                -7.244e-04  5.968e-04  -1.214 0.224843
## weather_regionClyde                  2.154e-03  1.013e-03   2.125 0.033562 *
## weather_regionPalmerston North       1.428e-02  9.019e-04  15.830  < 2e-16 ***
## weather_regionStratford              1.021e-02  1.137e-03   8.981  < 2e-16 ***
## weather_regionNapier                 5.695e-03  1.091e-03   5.219 1.82e-07 ***
## weather_regionInvercargill           2.330e-02  1.794e-03  12.987  < 2e-16 ***
## modelNissan Leaf (30 kWh)            2.676e-03  3.297e-04   8.119 4.95e-16 ***
## modelNissan Leaf (24 kWh) 2011-2012  1.655e-02  3.911e-04  42.329  < 2e-16 ***
## modelNissan Leaf (40 kWh)            1.024e-02  6.946e-04  14.740  < 2e-16 ***
## modelNissan e-NV200 (24 kWh)         3.190e-02  6.165e-04  51.748  < 2e-16 ***
## modelHyundai Ioniq (EV)             -1.762e-02  8.987e-04 -19.609  < 2e-16 ***
## modelBMW i3                         -1.437e-04  1.044e-03  -0.138 0.890478
## modelHyundai Kona (EV)               1.641e-03  1.228e-03   1.337 0.181361
## modelRenault Zoe                     1.103e-02  1.145e-03   9.630  < 2e-16 ***
## modelTesla Model 3                   1.222e-02  1.407e-03   8.682  < 2e-16 ***
## modelNissan Leaf (62 kWh)            2.676e-02  2.167e-03  12.350  < 2e-16 ***
## modelKia Niro (EV)                   1.132e-02  1.613e-03   7.015 2.36e-12 ***
## modelTesla Model S                   6.525e-02  1.991e-03  32.777  < 2e-16 ***
## modelVolkswagen e-Golf               2.498e-03  1.766e-03   1.415 0.157213
## modelConversion to EV                1.094e-01  2.796e-03  39.130  < 2e-16 ***
## modelTesla Model-X                   1.063e-01  2.188e-03  48.615  < 2e-16 ***
## modelKia Soul                        6.042e-03  1.822e-03   3.316 0.000915 ***
## modelMG ZS EV                        1.674e-02  4.977e-03   3.363 0.000772 ***
## modelRenault Kangoo (van)            6.082e-02  2.500e-03  24.332  < 2e-16 ***
## modelJaguar I-PACE                   7.709e-02  3.360e-03  22.943  < 2e-16 ***
## modelAudi A3 e-tron                  3.619e-02  6.810e-03   5.315 1.08e-07 ***
## modelMitsubishi iMiev - car          1.032e-01  1.364e-02   7.566 4.01e-14 ***
## modelPeugeot e-208                   1.074e-02  8.614e-03   1.247 0.212557
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01924 on 22793 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.4032, Adjusted R-squared:  0.4023
## F-statistic: 439.9 on 35 and 22793 DF,  p-value: < 2.2e-16
```


Residuals vs Fitted
Residuals
14804
0.15
0.20
0.25
Fitted values
lm((1/efficiency) ~ CDD + HDD + weather_region + model)


Normal Q−Q
Standardized residuals
14804
Theoretical Quantiles
lm((1/efficiency) ~ CDD + HDD + weather_region + model)





cooling degree days does explain extra variance but not much. likely as not many cooling days above 20 in nz

```
## Warning in anova.lmlist(object, ...): models with response '"(1/efficiency)"'
## removed because response differs from model 1
```

```
## Analysis of Variance Table
##
## Model 1: efficiency ~ HDD + model
## Model 2: efficiency ~ HDD + model
```

```
##   Res.Df   RSS Df Sum of Sq F Pr(>F)
## 1  22805 13456
## 2  22805 13456  0         0
```