

# Checking out the BG Climate Normals

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- Let's load in the data, and see what we've got. These were obtained from NOAA, and I stashed a copy so that I would have some control over it:

```
In[1049]:= BGNormals = Import[
            "http://ceadserv1.nku.edu/longa//classes/mat375/days/docs/Fletcher/data/
            BowlingGreenDailyClimateNormals.csv", "CSV"];
            BGheader = BGNormals[[1]]
            BGNormalData = BGNormals[[2 ;;]];
```

```
Out[1050]= {STATION, STATION_NAME, ELEVATION, LATITUDE, LONGITUDE, DATE,
            DLY-GRDD-BASE40, Completeness Flag, DLY-GRDD-BASE45, Completeness Flag,
            DLY-GRDD-BASE50, Completeness Flag, DLY-GRDD-BASE55, Completeness Flag,
            DLY-GRDD-BASE57, Completeness Flag, DLY-GRDD-BASE60, Completeness Flag,
            DLY-GRDD-BASE65, Completeness Flag, DLY-GRDD-BASE70, Completeness Flag,
            DLY-GRDD-BASE72, Completeness Flag, DLY-GRDD-TB4886, Completeness Flag,
            DLY-GRDD-TB5086, Completeness Flag, DLY-CLDD-BASE45, Completeness Flag,
            DLY-CLDD-BASE50, Completeness Flag, DLY-CLDD-BASE55, Completeness Flag,
            DLY-CLDD-BASE57, Completeness Flag, DLY-CLDD-BASE60, Completeness Flag,
            DLY-CLDD-NORMAL, Completeness Flag, DLY-CLDD-BASE70, Completeness Flag,
            DLY-CLDD-BASE72, Completeness Flag, DLY-HTDD-BASE40, Completeness Flag,
            DLY-HTDD-BASE45, Completeness Flag, DLY-HTDD-BASE50, Completeness Flag,
            DLY-HTDD-BASE55, Completeness Flag, DLY-HTDD-BASE57, Completeness Flag,
            DLY-HTDD-BASE60, Completeness Flag, DLY-HTDD-NORMAL, Completeness Flag,
            DLY-TAVG-NORMAL, Completeness Flag, DLY-DUTR-NORMAL, Completeness Flag,
            DLY-TMAX-NORMAL, Completeness Flag, DLY-TMIN-NORMAL, Completeness Flag,
            DLY-TAVG-STDDEV, Completeness Flag, DLY-DUTR-STDDEV, Completeness Flag,
            DLY-TMAX-STDDEV, Completeness Flag, DLY-TMIN-STDDEV, Completeness Flag}
```

---

Now I want to pick off the important variables: max, min,

## and dtr.

```

In[1052]:= (* Dumb counting method...: *)
  navg = 13 * 4 + 6 + 1;
  ndtr = navg + 2;
  nmax = navg + 4;
  nmin = navg + 6;
  navgstddev = navg + 8;
  ndtrstddev = navg + 10;
  nmaxstddev = navg + 12;
  nminstddev = navg + 14;
  indices = {navg, ndtr, nmax, nmin, navgstddev, ndtrstddev, nmaxstddev, nminstddev};
  vnames = BGheader[[indices]]

Out[1061]= {DLY-TAVG-NORMAL, DLY-DUTR-NORMAL, DLY-TMAX-NORMAL, DLY-TMIN-NORMAL,
  DLY-TAVG-STDDEV, DLY-DUTR-STDDEV, DLY-TMAX-STDDEV, DLY-TMIN-STDDEV}

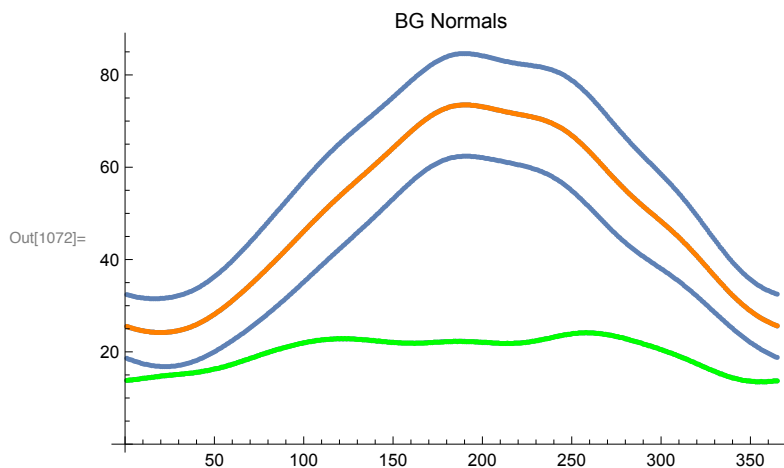
In[1062]:= BGNormalTemps = BGNormalData[[All, indices]];
  BGNormalTemps[[1, All]]
  {avg, dtr, max, min, avgstddev, dtrstddev, maxstddev, minstddev} =
  Transpose[BGNormalTemps];

Out[1063]= {25.5, 13.8, 32.4, 18.6, 11, 6.4, 11.2, 11.9}

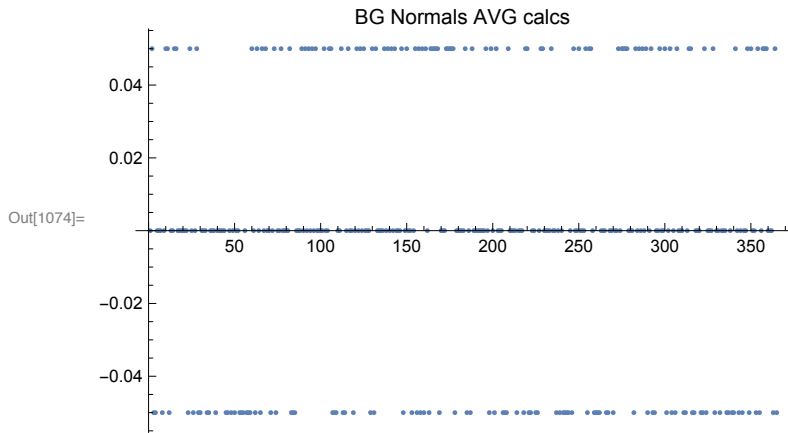
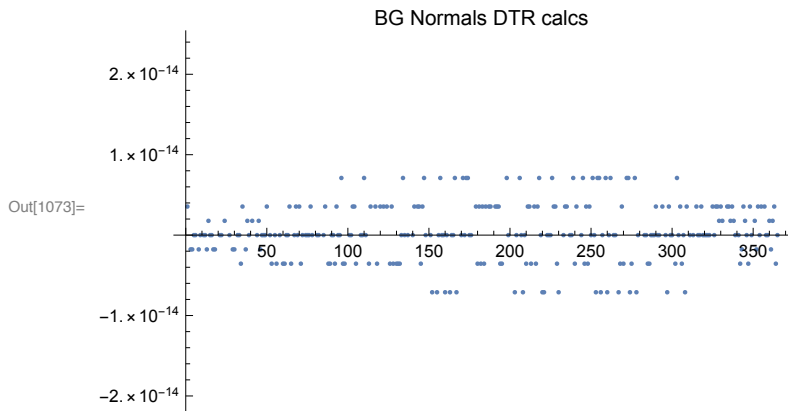
```

Averages and DTR, presented as data in the data set, are actually just derived from max and min normals, as these commands show:

```
In[1065]:= days = Table[i, {i, 1, 365}];
p1 = ListPlot[Transpose[{days, min}], PlotLabel -> "BG Normals"];
p2 = ListPlot[Transpose[{days, avg}], PlotLabel -> "BG Normal Mean"];
p3 = ListPlot[Transpose[{days, max}], PlotLabel -> "BG Normal Mean"];
p4 = ListPlot[Transpose[{days, dtr}], PlotLabel -> "BG Normals"];
p5 = ListPlot[Transpose[{days, max - min}],
  PlotLabel -> "BG Normals", PlotStyle -> Green];
p6 = ListPlot[Transpose[{days, (max + min) / 2}],
  PlotLabel -> "BG Normals", PlotStyle -> Orange];
Show[p1, p2, p3, p4, p5, p6, PlotRange -> All]
```



```
In[1073]:= ListPlot[Transpose[{days, dtr - (max - min)}], PlotLabel -> "BG Normals DTR calcs"]  
ListPlot[Transpose[{days, avg - (max + min) / 2}], PlotLabel -> "BG Normals AVG calcs"]
```



## ■ Now let's do some regression:

### Regressions for Minimum Normals

We can do the regressions either as linear regressions, or as non-linear regressions -- and we'll get exactly the same results! It's because of the magic of the trig identity, which allows us to break the  $\text{Sin}[2\pi(t-t_0)]$  term into Sine and Cosine terms.

If we do them as linear regressions, the R-squared terms are more useful.

This first regression just fits  
 $a + b \text{Cos}[2 \text{Pi } x] + c \text{Sin}[2\text{Pi } x]$

```
In[1075]:= pointOfYear = days / 365;
data = Transpose[{pointOfYear, min}];
minplot = ListPlot[data, PlotLabel -> "Minimum -- BG Normals"];
minlm = LinearModelFit[Cases[data, {_?NumericQ..}], {Cos[2 Pi x], Sin[2 Pi x]}, x]
minfits = minlm["FitResiduals"];
minlm["ParameterTable"]
minlm["RSquared"]
minlm["AdjustedRSquared"]
minlm["ParameterConfidenceIntervals"]
Show[minplot, Plot[minlm[x], {x, 0, 1}]]
Histogram[minfits]
```

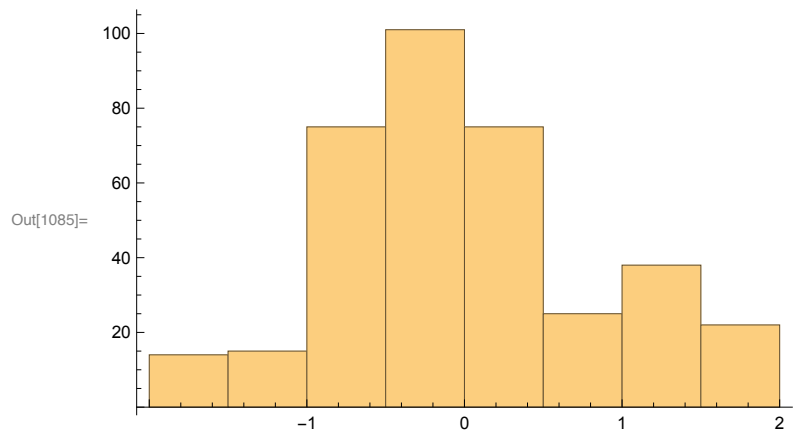
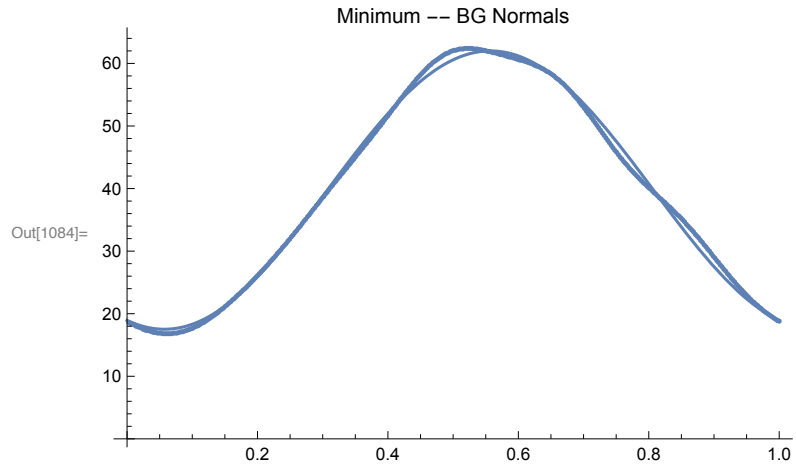
```
Out[1078]= FittedModel[ 39.7551 - 20.8182 Cos[2 π x] - 7.81826 Sin[2 π x]
```

	Estimate	Standard Error	t-Statistic	P-Value
1	39.7551	0.0429371	925.891	0.
Cos[2 π x]	-20.8182	0.0607222	-342.844	0.
Sin[2 π x]	-7.81826	0.0607222	-128.755	$2.09402 \times 10^{-304}$

```
Out[1081]= 0.997308
```

```
Out[1082]= 0.997293
```

```
Out[1083]= {{39.6706, 39.8395}, {-20.9376, -20.6988}, {-7.93768, -7.69885}}
```



This second regression adds a linear term (d x):

$$a + d x + b \cos[2 \pi x] + c \sin[2 \pi x]$$

and we discover that the d is significantly different from 0, and positive -- 1.9, which, on an annual basis would represent quite an amazing increase in minimum temperature!

```
In[1086]:= minlm = LinearModelFit[Cases[data, {_?NumericQ..}], {x, Cos[2 Pi x], Sin[2 Pi x]}, x]
minfits = minlm["FitResiduals"];
minlm["ParameterTable"]
minlm["RSquared"]
minlm["AdjustedRSquared"]
minlm["ParameterConfidenceIntervals"]
Show[minplot, Plot[minlm[x], {x, 0, 1}]]
Histogram[minfits]
```

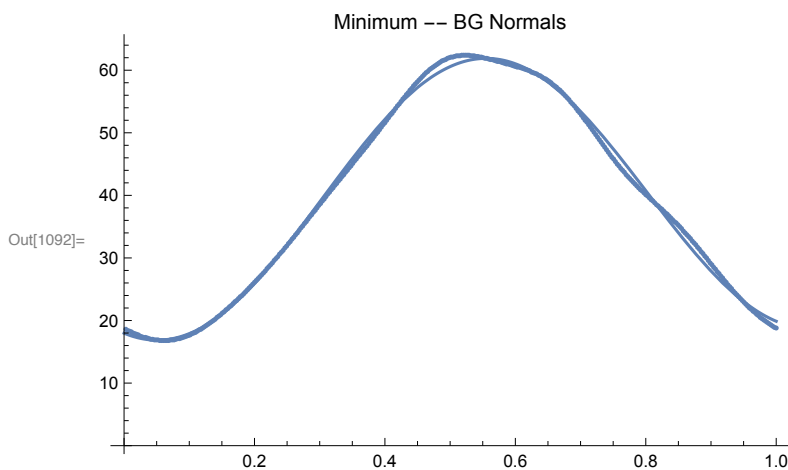
```
Out[1086]= FittedModel [ 38.8011 + 1.90273 x - 20.8234 Cos[2 π x] - 7.21262 Sin[2 π x] ]
```

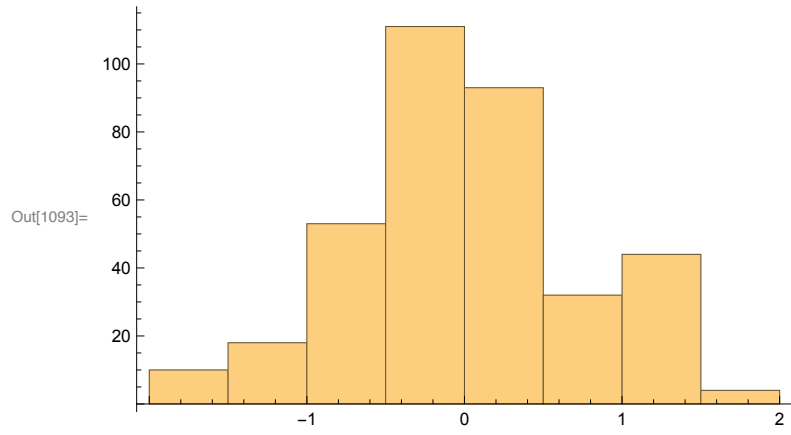
	Estimate	Standard Error	t-Statistic	P-Value
1	38.8011	0.114996	337.412	0.
Out[1088]= x	1.90273	0.21577	8.81833	5.02075 × 10 <sup>-17</sup>
Cos[2 π x]	-20.8234	0.0551584	-377.521	0.
Sin[2 π x]	-7.21262	0.0880855	-81.8821	3.10506 × 10 <sup>-235</sup>

```
Out[1089]= 0.997785
```

```
Out[1090]= 0.997767
```

```
Out[1091]= {{38.5749, 39.0272}, {1.47841, 2.32706}, {-20.9319, -20.715}, {-7.38585, -7.0394}}
```







Now I'll do the regression using non-linear regression. In a way, it's cleaner: I don't need to deduce the amplitude and phase shift -- I'm staring at them! The results are identical, however -- and that's one of the cool things.

Again, the first model is -- well, there it is in the command for `NonlinearModelFit`! I like the way we write the regression model with `NonlinearModelFit`.

```
In[1094]= minlm = NonlinearModelFit[data, {a + amp Sin[2 Pi (x - x0)]}, {a, amp, {x0, .3}}, x]
minfits = minlm["FitResiduals"];
minlm["ParameterTable"]
minlm["RSquared"]
minlm["AdjustedRSquared"]
minlm["ParameterConfidenceIntervals"]
Show[minplot, Plot[minlm[x], {x, 0, 1}]]
Histogram[minfits]
```

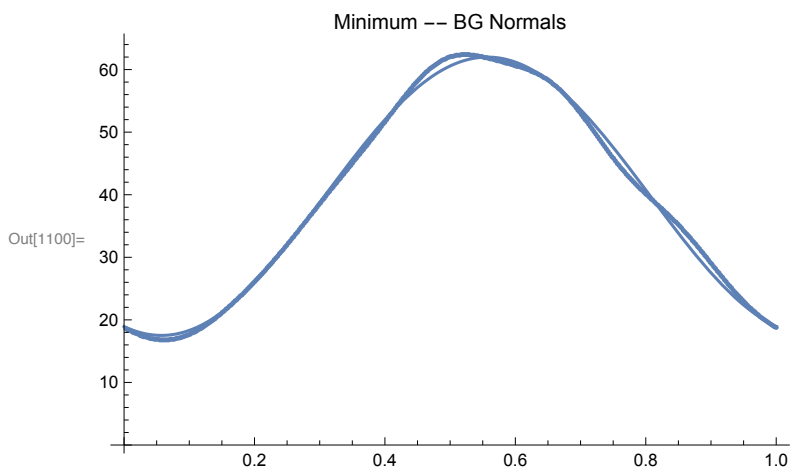
```
Out[1094]= FittedModel [ 39.7551 + 22.2379 Sin[2 π (-0.307177 + x)] ]
```

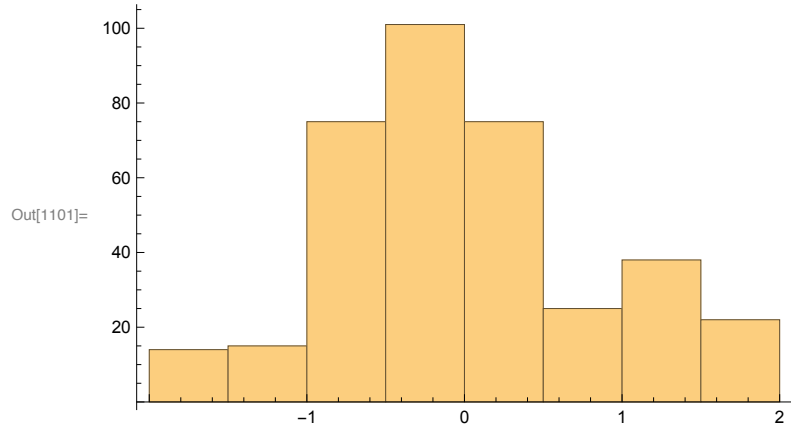
	Estimate	Standard Error	t-Statistic	P-Value
a	39.7551	0.0429371	925.891	0.
amp	22.2379	0.0607222	366.224	0.
x0	0.307177	0.000434584	706.829	0.

```
Out[1097]= 0.999635
```

```
Out[1098]= 0.999632
```

```
Out[1099]= {{39.6706, 39.8395}, {22.1185, 22.3573}, {0.306322, 0.308031}}
```





Our model has an amplitude of 22.24 (a total variation of twice that), and the curve hits its mean at .3063 of the year; that means it bottoms out at .3063-.25 of the year, or .0563\*365.25 -- about the 21st of January.

As before, we now add the linear term, only doing so with NonlinearModelFit.

```
In[1102]:= minlm = NonlinearModelFit[data,
  {a + b x + amp Sin[2 Pi (x - x0)]}, {a, b, amp, {x0, .3}}, x]
minfits = minlm["FitResiduals"];
minlm["ParameterTable"]
minlm["RSquared"]
minlm["AdjustedRSquared"]
minlm["ParameterConfidenceIntervals"]
Show[minplot, Plot[minlm[x], {x, 0, 1}]]
Histogram[minfits]
```

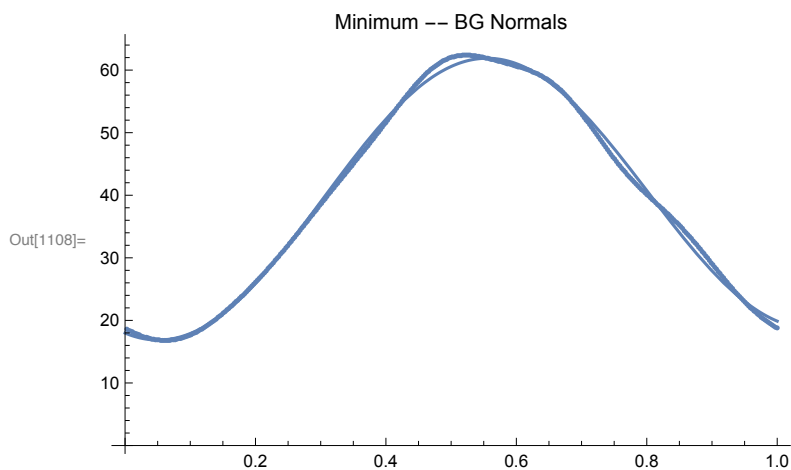
```
Out[1102]= FittedModel [ 38.8011 + 1.90273 x + 22.0372 Sin[2 π(-0.303068 + x)] ]
```

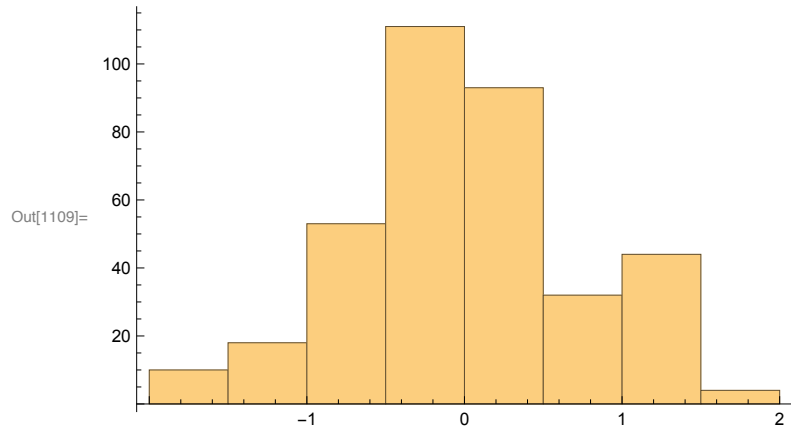
	Estimate	Standard Error	t-Statistic	P-Value
a	38.8011	0.114996	337.412	0.
b	1.90273	0.21577	8.81833	$5.02075 \times 10^{-17}$
amp	22.0372	0.0593514	371.301	0.
x0	0.303068	0.000616165	491.862	0.

```
Out[1105]= 0.9997
```

```
Out[1106]= 0.999696
```

```
Out[1107]= {{38.5749, 39.0272}, {1.47841, 2.32706}, {21.9205, 22.1539}, {0.301856, 0.30428}}
```





## Regressions for Maximum Normals

I'm now going to reproduce the same type of results for the maxima, rather than the minima.

```
In[1110]:= data = Transpose[{pointOfYear, max}];
maxplot = ListPlot[data, PlotLabel -> "Maximum -- BG Normals"];
maxlm = LinearModelFit[data, {Cos[2 Pi x], Sin[2 Pi x]}, x]
maxfits = maxlm["FitResiduals"];
maxlm["ParameterTable"]
maxlm["RSquared"]
maxlm["AdjustedRSquared"]
maxlm["ParameterConfidenceIntervals"]
Show[maxplot, Plot[maxlm[x], {x, 0, 1}]]
Histogram[maxfits]
```

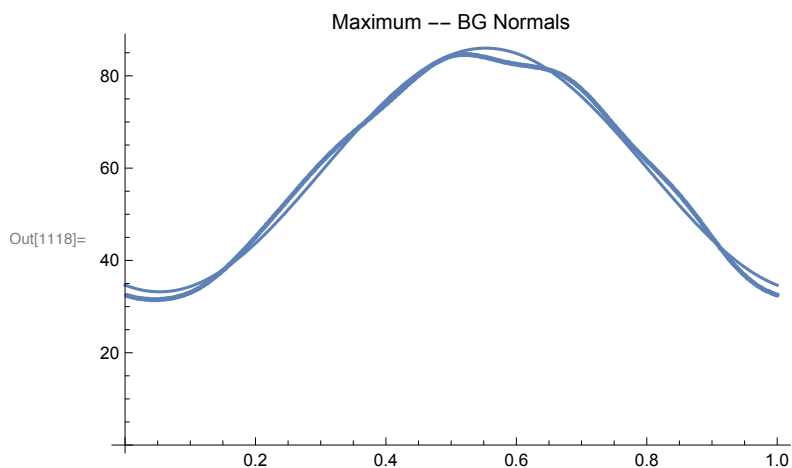
```
Out[1112]= FittedModel [ 59.6011 - 24.9441 Cos[2 πx] - 8.63393 Sin[2 πx] ]
```

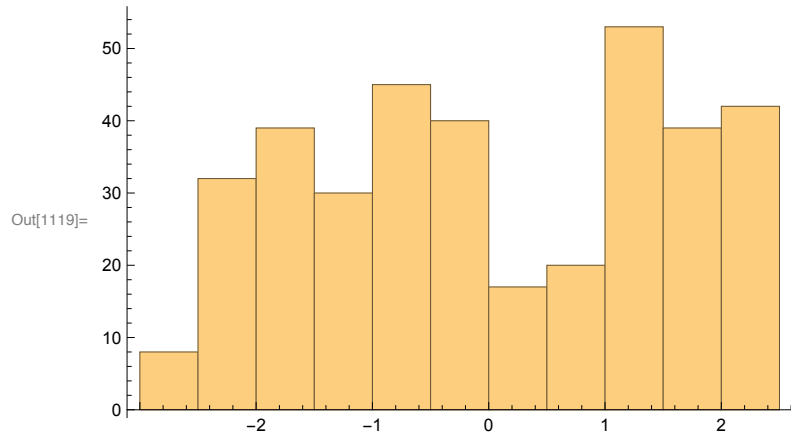
	Estimate	Standard Error	t-Statistic	P-Value
1	59.6011	0.0790277	754.18	0.
Cos[2 πx]	-24.9441	0.111762	-223.189	0.
Sin[2 πx]	-8.63393	0.111762	-77.2527	$5.09779 \times 10^{-227}$

```
Out[1115]= 0.993552
```

```
Out[1116]= 0.993517
```

```
Out[1117]= {{59.4457, 59.7565}, {-25.1639, -24.7243}, {-8.85371, -8.41414}}
```





```

In[1120]:= maxlm = LinearModelFit[data, {x, Cos[2 Pi x], Sin[2 Pi x]}, x]
maxfits = maxlm["FitResiduals"];
maxlm["ParameterTable"]
maxlm["RSquared"]
maxlm["AdjustedRSquared"]
maxlm["ParameterConfidenceIntervals"]
Show[maxplot, Plot[maxlm[x], {x, 0, 1}]]
Histogram[maxfits]

```

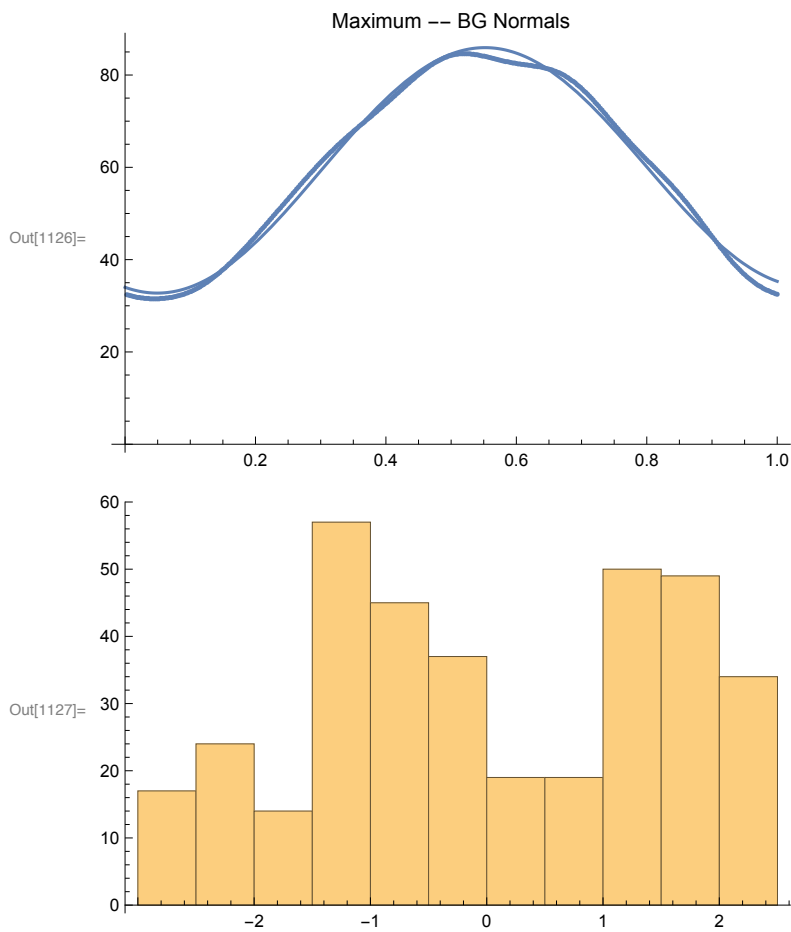
```
Out[1120]= FittedModel[58.9558 + 1.28703 x - 24.9476 Cos[2 π x] - 8.22426 Sin[2 π x]]
```

	Estimate	Standard Error	t-Statistic	P-Value
1	58.9558	0.230532	255.739	0.
x	1.28703	0.432552	2.97543	0.00312278
Cos[2 π x]	-24.9476	0.110576	-225.616	0.
Sin[2 π x]	-8.22426	0.176584	-46.5742	$1.04268 \times 10^{-154}$

```
Out[1123]= 0.993707
```

```
Out[1124]= 0.993654
```

```
Out[1125]= {{58.5025, 59.4092}, {0.436392, 2.13767}, {-25.1651, -24.7302}, {-8.57152, -7.877}}
```



So we notice that the linear term is 1.28 or so; it's significantly different from

zero. Maxima are increasing over the course of the year.

But not nearly as much as the minima, for which it was almost 2: minima were increasing twice as fast as maxima, according to these models.

```
In[1128]:= maxlm = NonlinearModelFit[data, {a + amp Sin[2 Pi (x - x0)]}, {a, amp, {x0, .3}}, x]
maxfits = maxlm["FitResiduals"];
maxlm["ParameterTable"]
maxlm["RSquared"]
maxlm["AdjustedRSquared"]
maxlm["ParameterConfidenceIntervals"]
Show[maxplot, Plot[maxlm[x], {x, 0, 1}]]
Histogram[maxfits]
```

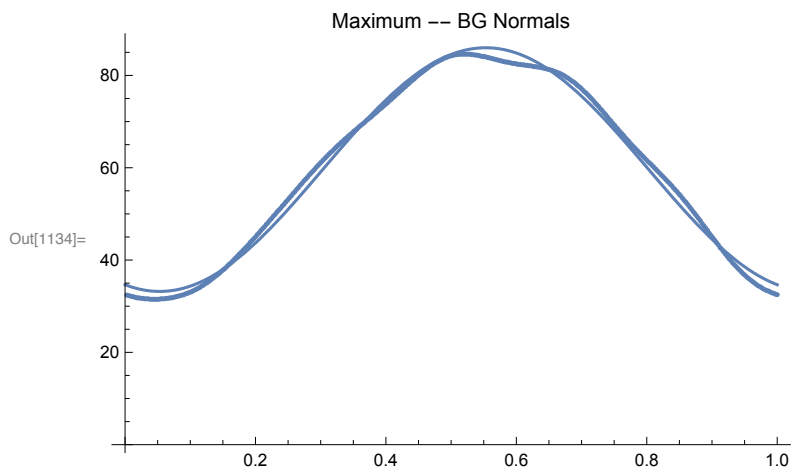
```
Out[1128]= FittedModel [ 59.6011 + 26.3961 Sin[2 π (-0.303034 + x)] ]
```

	Estimate	Standard Error	t-Statistic	P-Value
Out[1130]= a	59.6011	0.0790277	754.18	0.
amp	26.3961	0.111762	236.181	0.
x0	0.303034	0.000673868	449.693	0.

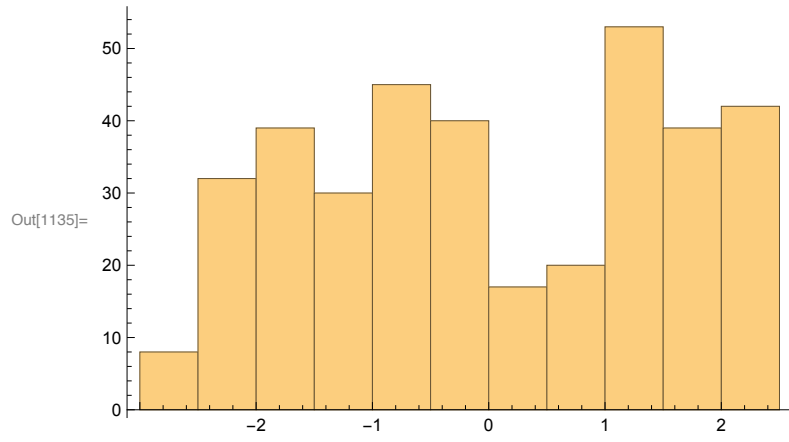
```
Out[1131]= 0.999421
```

```
Out[1132]= 0.999416
```

```
Out[1133]= {{59.4457, 59.7565}, {26.1763, 26.6159}, {0.301709, 0.304359}}
```







Our model has an amplitude of 26.40 (a total variation of twice that), and the curve hits its mean at .3030 of the year; that means it bottoms out at .3030-.25 of the year, or .0530\*365.25 -- about the 19th of January.

As before, we now add the linear term, only doing so with `NonlinearModelFit`.

```
In[1136]:= maxlm = NonlinearModelFit[data,
  {a + b x + amp Sin[2 Pi (x - x0)]}, {a, b, amp, {x0, .3}}, x]
maxfits = maxlm["FitResiduals"];
maxlm["ParameterTable"]
maxlm["RSquared"]
maxlm["AdjustedRSquared"]
maxlm["ParameterConfidenceIntervals"]
Show[maxplot, Plot[maxlm[x], {x, 0, 1}]]
Histogram[maxfits]
```

```
Out[1136]= FittedModel[ 58.9558 + 1.28703 x + 26.2683 Sin[2 π(-0.300682 + x)] ]
```

	Estimate	Standard Error	t-Statistic	P-Value
Out[1138]= a	58.9558	0.230532	255.739	0.
b	1.28703	0.432552	2.97543	0.00312278
amp	26.2683	0.118271	222.103	0.
x0	0.300682	0.00103924	289.328	0.

```
Out[1139]= 0.999435
```

```
Out[1140]= 0.999428
```

```
Out[1141]= {{58.5025, 59.4092}, {0.436392, 2.13767}, {26.0357, 26.5009}, {0.298638, 0.302725}}
```

