Analyze whether early or late snow changes more year to year or place to place.

- We know from previous notebooks that the value of `coef_2` corresponds to whether the snow season is early or late.
- We want to study whether early/late season is more dependent on the year or the location
- We will use RMS Error to quantify the strength of these dependencies

```
In [1]: state='NY'
        meas='SNWD'
```

In [6]:
```python
#extract longitude and latitude for each station
feature='coeff_1'
sqlContext.registerDataFrameAsTable(decomposition,'decomposition')
Features='station, year, coeff_2'
Query="SELECT %s FROM decomposition"%Features
print(Query)
pdf = sqlContext.sql(Query).toPandas()
pdf.head()
```

```
SELECT station, year, coeff_2 FROM decomposition
```

Out[6]:

	station	year	coeff_2
0	US1NYDT0024	2022	-32.220312
1	US1NYHR0016	2022	46.982097
2	US1NYJF0030	2022	777.557999
3	US1NYMG0003	2022	-21.670491
4	US1NYMR0026	2022	340.964617

The Pivot

An operation for creating an XY table from a list.

In [7]:
```
year_station_table=pdf.pivot(index='year', columns='station', values='coeff_2')
year_station_table.tail(3)
```

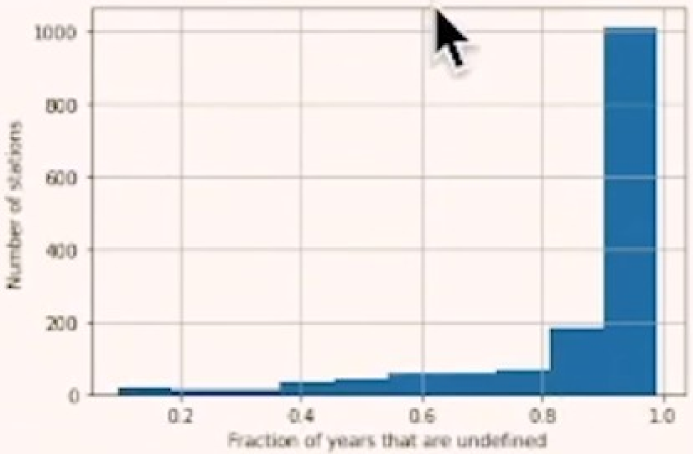
Out[7]:

station	US1NYAB0001	US1NYAB0006	US1NYAB0010	US1NYAB0016	US1NYAB0021	US1NYAB0022	US1NYAB0023	US1NYAB0025	US1NYAI
year									
2020	162.934900	NaN	0.318085	NaN	-207.460436	NaN	-242.322141	NaN	NaN
2021	272.389446	NaN	-6.088038	NaN	69.424530	NaN	119.285450	NaN	NaN
2022	275.131390	NaN	1.373080	NaN	-169.532332	NaN	-29.564078	NaN	NaN

3 rows × 1506 columns

In [8]:
```
station_nulls=pd.isnull(year_station_table).mean()
station_nulls.hist();
xlabel('Fraction of years that are undefined')
ylabel('Number of stations')
```

Out[8]:
```
Text(0, 0.5, 'Number of stations')
```



In [9]:
```
year_nulls=pd.isnull(year_station_table).mean(axis=1)
year_nulls.plot();
grid()
ylabel('fraction of stations that are undefined')
```

Out[9]:
```
Text(0, 0.5, 'fraction of stations that are undefined')
```

In [10]:
```
pdf2=pdf[pdf['year']>1960]
year_station_table=pdf2.pivot(index='year', columns='station', values='coeff_2')
year_station_table.tail(5)
```

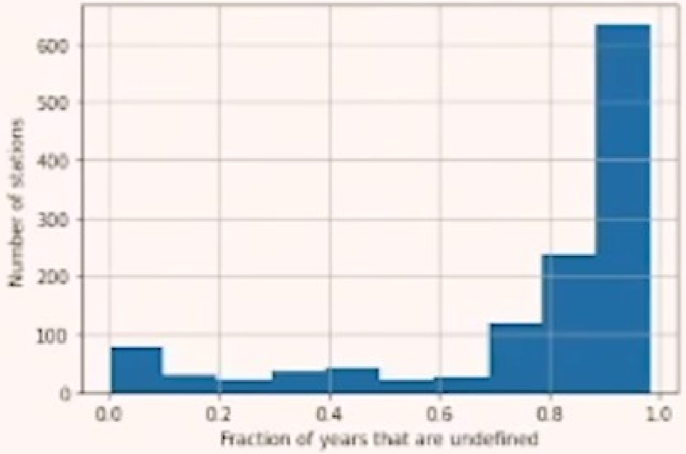
Out[10]:

station	US1NYAB0001	US1NYAB0006	US1NYAB0010	US1NYAB0016	US1NYAB0021	US1NYAB0022	US1NYAB0023	US1NYAB0025	US1NYAI
year									
2018	-971.259732	-31.420069	-2.725126	NaN	-310.500205	NaN	-551.346264	NaN	NaN
2019	21.911582	3.865887	1.881955	NaN	-94.416242	NaN	153.801254	NaN	NaN
2020	162.934900	NaN	0.318085	NaN	-207.460436	NaN	-242.322141	NaN	NaN
2021	272.389446	NaN	-6.088038	NaN	69.424530	NaN	119.285450	NaN	NaN
2022	275.131390	NaN	1.373080	NaN	-169.532332	NaN	-29.564078	NaN	NaN

5 rows × 1248 columns

In [11]:
```
station_nulls=pd.isnull(year_station_table).mean()
station_nulls.hist();
xlabel('Fraction of years that are undefined')
ylabel('Number of stations')
```

Out[11]: `Text(0, 0.5, 'Number of stations')`



Estimating the effect of the year vs the effect of the station

To estimate the effect of time vs. location on the second eigenvector coefficient we compute:

- The average row: `mean-by-station`
- The average column: `mean-by-year`

We then compute the RMS before and after subtracting either the row or the column vector.

In [12]:

```
: RMS(Mat):
 return np.sqrt(np.nanmean(Mat**2))

ın_by_year=np.nanmean(year_station_table,axis=1)
ın_by_station=np.nanmean(year_station_table,axis=0)
._minus_year = (year_station_table.transpose()-mean_by_year).transpose()
._minus_station = year_station_table-mean_by_station

.nt('total RMS                    = ',RMS(year_station_table))
.nt('RMS removing mean-by-station= ',RMS(tbl_minus_station),'reduction=',RMS(year_station_table)-RMS(tb
.nt('RMS removing mean-by-year    = ',RMS(tbl_minus_year),'reduction=',RMS(year_station_table)-RMS(tbl_m
```

```
total RMS                    =  489.524439882916
RMS removing mean-by-station=  466.3497380540662 reduction= 23.174701828849777
RMS removing mean-by-year    =  400.56360877189684 reduction= 88.96083111101916
```

Conclusion Of Analysis

The effect of time is about four times as large as the effect of location.

Iterative reduction

- After removing one component, the other component can have an effect.
- We can use **alternating minimization** to remove the combined effect of location and time.

In [13]:
```
T=year_station_table
print('initial RMS=',RMS(T))
for i in range(5):
    mean_by_year=np.nanmean(T,axis=1)
    std_by_year=np.nanstd(T,axis=1)
    T=(T.transpose()-mean_by_year).transpose()
    print(i,'after removing mean by year    =',RMS(T))
    mean_by_station=np.nanmean(T,axis=0)
    T=T-mean_by_station
    print(i,'after removing mean by stations=',RMS(T))
```

```
initial RMS= 489.524439882916
0 after removing mean by year    = 400.56360877189684
0 after removing mean by stations= 377.0618726106545
1 after removing mean by year    = 376.9834108042794
1 after removing mean by stations= 376.96797710124497
2 after removing mean by year    = 376.96074510568275
2 after removing mean by stations= 376.9562378360024
3 after removing mean by year    = 376.9532516568049
3 after removing mean by stations= 376.9512457701175
4 after removing mean by year    = 376.94989312806547
4 after removing mean by stations= 376.94897974011
```

In [14]:
```
years=list(T.index)
plot(years,mean_by_year)
grid()
title('mean as a function of year')
```

Out[14]:
```
Text(0.5, 1.0, 'mean as a function of year')
```

Is this conclusion justified?

Check the graph for individual stations

In [15]:
```
for i in range(10):
    plot(years,T.iloc[:,i])
grid()
title('3rd coefficient as function of time for several stations');
```

Summary

- After removing one component, the other component can have an effect.
- RMS can be used to quantify the effect of different factors (here, time vs. space)
- The snow season in NY seems to be getting earlier and earlier since 1960.
- but the high variance places doubt on this conclusion.