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In [154]:
```
import numpy as np
import pandas as pd
import wbgapi as wb
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn.cluster as cluster
import scipy.optimize as opt
import itertools as iter

import warnings
warnings.filterwarnings("ignore")
```

In [155]:
```
country_codes = ["GBR","AUS","USA","DEU","FRA","JPN","KOR","CAN","CHE","TUR","ESP

country_names = {
    "GBR" : "United Kingdom",
    "AUS" : "Australia",
    "USA" : "United States",
    "DEU" : "Germany",
    "FRA" : "France",
    "JPN" : "Japan",
    "KOR" : "South Korea",
    "CAN" : "Canada",
    "CHE" : "Switzerland",
    "TUR" : "Turkey",
    "ESP" : "Spain",
    "ITA" : "Italy"
}

#Agricultural land (% of land area)
#Crop production
#Food production
indicators=['AG.LND.AGRI.ZS','AG.PRD.CROP.XD','AG.PRD.FOOD.XD']
```

In [156]:

```
# This function retrieves data from world bank website and saves it into a file
def bank_data(data):
    print(wb.series.info(indicators))

    years = np.array(range(1970,2019))

    #MultiIndex Columns
    columns=pd.MultiIndex.from_arrays([['Agricultural_land','Crop_production',
                                        'Food_production'],
                                          ['','','']])
    #MultiIndex Rows
    eco_index = pd.MultiIndex.from_product([data, years],
                                   names=['Country', 'Year'])

    df_production = pd.DataFrame()

    for all_data in data:
        df_cli = wb.data.DataFrame(indicators, all_data, time=range(1970,2019)).s
        #use concat hierarchical indexing
        df_production = pd.concat([df_production, df_cli.T], ignore_index=True)

    df_production = df_production.set_index(eco_index)

    # Checking for null values in dataframe
    display("Checking null values in DataFrame")
    display(df_production.isnull().sum())

    return df_production
```

In [157]:
```
final_df = bank_data(country_codes)
final_df
```

```
id              value
--------------  ---------------------------------------
AG.LND.AGRI.ZS  Agricultural land (% of land area)
AG.PRD.CROP.XD  Crop production index (2014-2016 = 100)
AG.PRD.FOOD.XD  Food production index (2014-2016 = 100)
                3 elements

'Checking null values in DataFrame'

Agricultural_land      0
Crop_production        0
Food_production        0
dtype: int64
```

Out[157]:

| | | Agricultural_land | Crop_production | Food_production |
|---|---|---|---|---|
| **Country** | **Year** | | | |
| | **1970** | 77.910966 | 70.529999 | 77.970001 |
| | **1971** | 77.886165 | 73.989998 | 79.190002 |
| **GBR** | **1972** | 77.526557 | 71.080002 | 80.269997 |
| | **1973** | 77.278552 | 73.870003 | 81.239998 |
| | **1974** | 77.038813 | 76.220001 | 84.769997 |
| **...** | **...** | ... | ... | ... |
| | **2014** | 44.747399 | 95.400002 | 95.580002 |
| | **2015** | 44.009655 | 103.059998 | 102.550003 |
| **ITA** | **2016** | 43.557490 | 101.540001 | 101.879997 |
| | **2017** | 43.607024 | 96.940002 | 98.070000 |
| | **2018** | 41.665267 | 95.150002 | 98.910004 |

588 rows × 3 columns

In [158]:
```
final_df.groupby('Country').describe().T
```

Out[158]:

| | Country | AUS | CAN | CHE | DEU | ESP | FR |
|---|---|---|---|---|---|---|---|
| Agricultural_land | count | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.00000 |
| | mean | 58.259455 | 6.793882 | 40.238786 | 50.523189 | 59.564984 | 55.6006 |
| | std | 6.316012 | 0.185615 | 1.261064 | 2.341447 | 3.683630 | 2.3725 |
| | min | 44.539926 | 6.435684 | 38.214254 | 47.641536 | 52.408210 | 52.3417 |
| | 25% | 51.853677 | 6.757391 | 39.142647 | 48.594861 | 57.342980 | 53.5336 |
| | 50% | 60.383088 | 6.833125 | 40.142680 | 49.640453 | 60.345587 | 55.1621 |
| | 75% | 63.883472 | 6.893133 | 41.524995 | 52.690975 | 62.449445 | 57.7939 |
| | max | 65.181261 | 7.044824 | 42.347197 | 54.486867 | 65.396775 | 59.5782 |
| Crop_production | count | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.00000 |
| | mean | 67.154286 | 62.104082 | 113.120000 | 90.664285 | 81.226122 | 92.8359 |
| | std | 23.693385 | 21.087347 | 13.459657 | 7.381608 | 16.670734 | 8.5101 |
| | min | 31.360001 | 30.680000 | 92.169998 | 74.239998 | 50.980000 | 72.0199 |
| | 25% | 49.119999 | 46.400002 | 103.059998 | 84.610001 | 68.720001 | 89.2799 |
| | 50% | 59.869999 | 58.900002 | 111.300003 | 91.489998 | 81.290001 | 94.1500 |
| | 75% | 88.239998 | 72.870003 | 122.400002 | 95.510002 | 94.529999 | 99.5100 |
| | max | 121.239998 | 108.019997 | 152.089996 | 107.610001 | 121.690002 | 105.9899 |
| Food_production | count | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.000000 | 49.00000 |
| | mean | 71.736123 | 69.242858 | 98.539388 | 93.981837 | 78.605510 | 97.6748 |
| | std | 17.264626 | 18.288463 | 5.127825 | 5.670311 | 17.397420 | 6.5068 |
| | min | 45.020000 | 41.340000 | 85.269997 | 83.339996 | 46.520000 | 82.7500 |
| | 25% | 58.060001 | 55.779999 | 95.339996 | 89.309998 | 64.449997 | 95.8499 |
| | 50% | 68.480003 | 65.889999 | 98.529999 | 94.139999 | 76.720001 | 99.2399 |
| | 75% | 86.620003 | 82.000000 | 101.830002 | 97.500000 | 93.459999 | 102.0299 |
| | max | 104.040001 | 108.370003 | 108.660004 | 106.830002 | 117.860001 | 107.5999 |

In [159]:

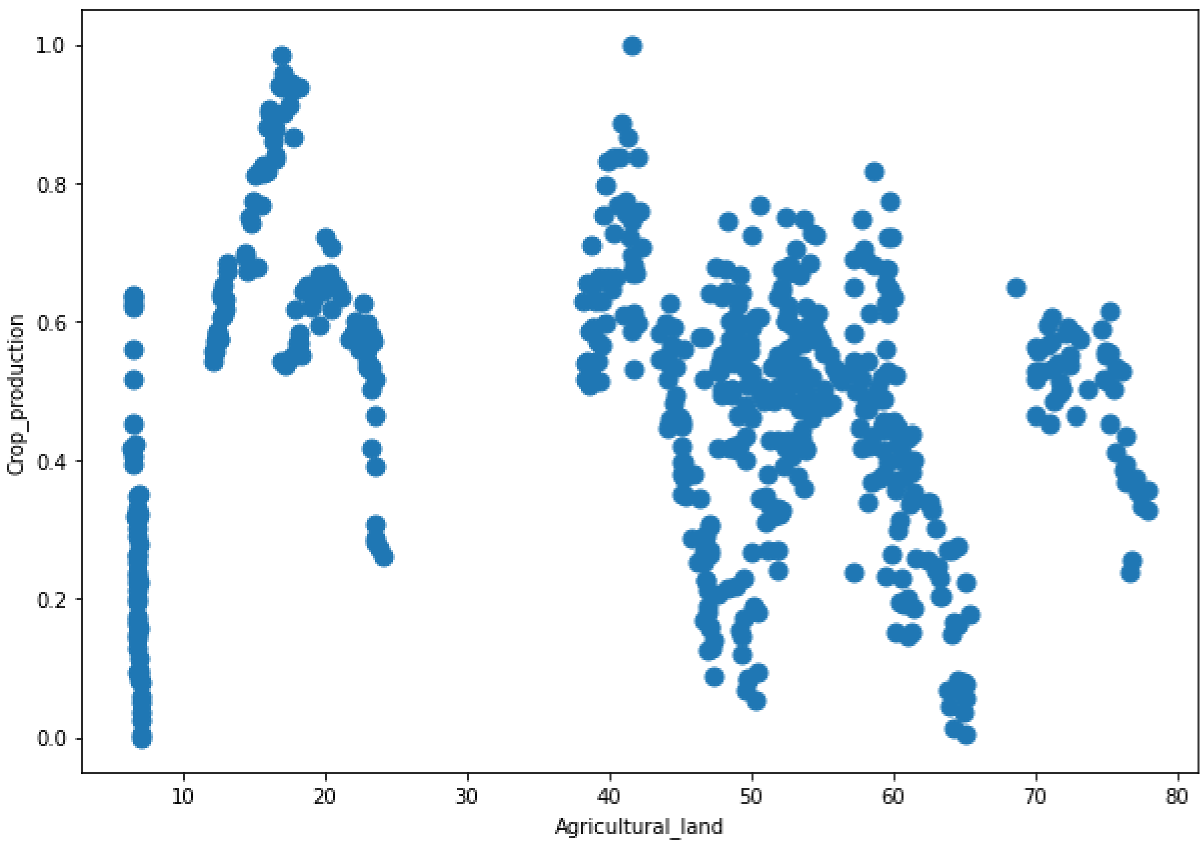
```
def norm(array):
    min_val = np.min(array)
    max_val = np.max(array)

    scaled = (array-min_val) / (max_val-min_val)

    return scaled

def norm_df(df):
    # iterate over all columns
    for col in df.columns[1:]:     # excluding the first column
        df[col] = norm(df[col])

    return df
```

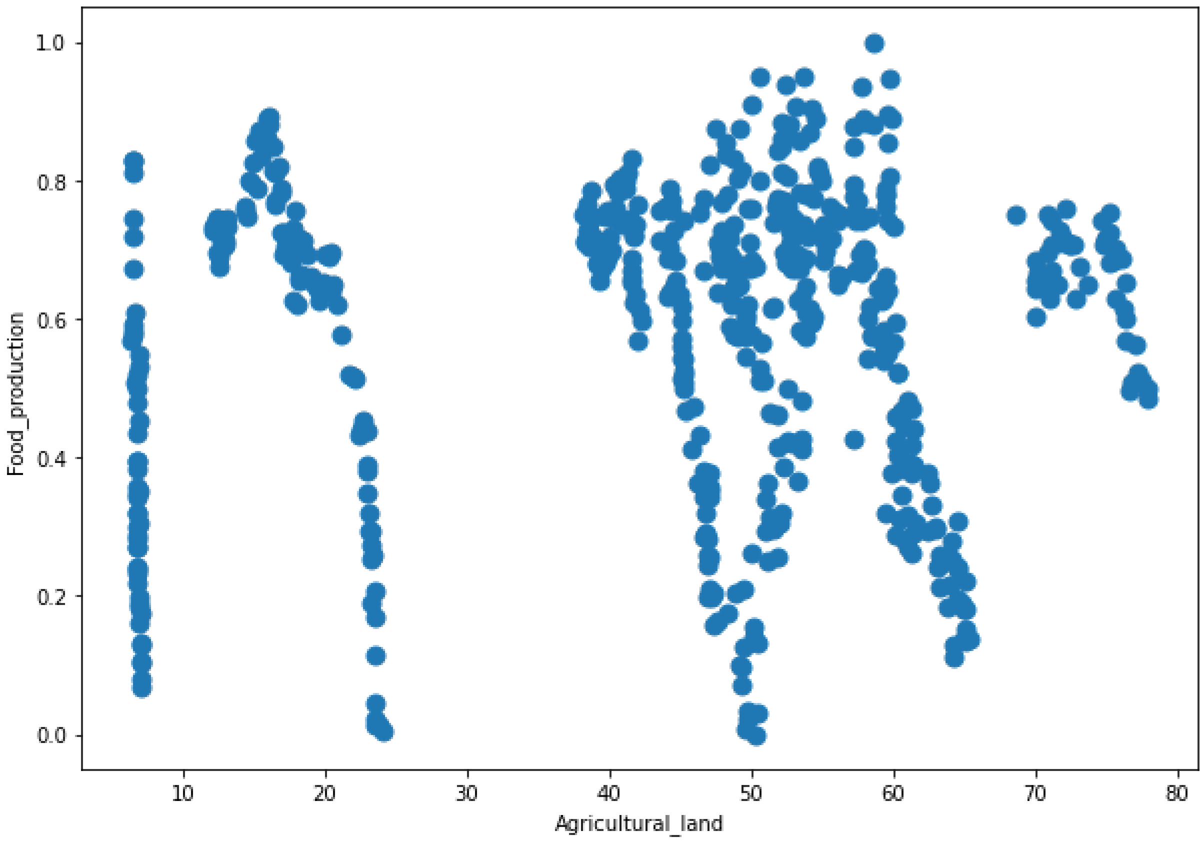
In [160]:

```
# normalise result and inspect results
normalised_df = norm_df(final_df)
print(normalised_df.describe())
print()
```

```
      Agricultural_land Crop_production Food_production

count        588.000000      588.000000      588.000000
mean          44.253281        0.482929        0.575915
std           19.453966        0.198634        0.220691
min            6.435684        0.000000        0.000000
25%           34.683912        0.350404        0.411393
50%           49.325650        0.517750        0.650675
75%           57.848934        0.606004        0.734774
max           77.910966        1.000000        1.000000
```

In [161]:
```
def makeplot(df, col1, col2):
    plt.figure(figsize=(10.0,7.0))
    plt.plot(df[col1], df[col2], "o", markersize=9)

    plt.xlabel(col1)
    plt.ylabel(col2)
    plt.savefig(f'{col1}_dataplot.jpg')

    plt.show()

makeplot(normalised_df, "Agricultural_land", "Crop_production")
makeplot(normalised_df, "Agricultural_land", "Food_production")
```

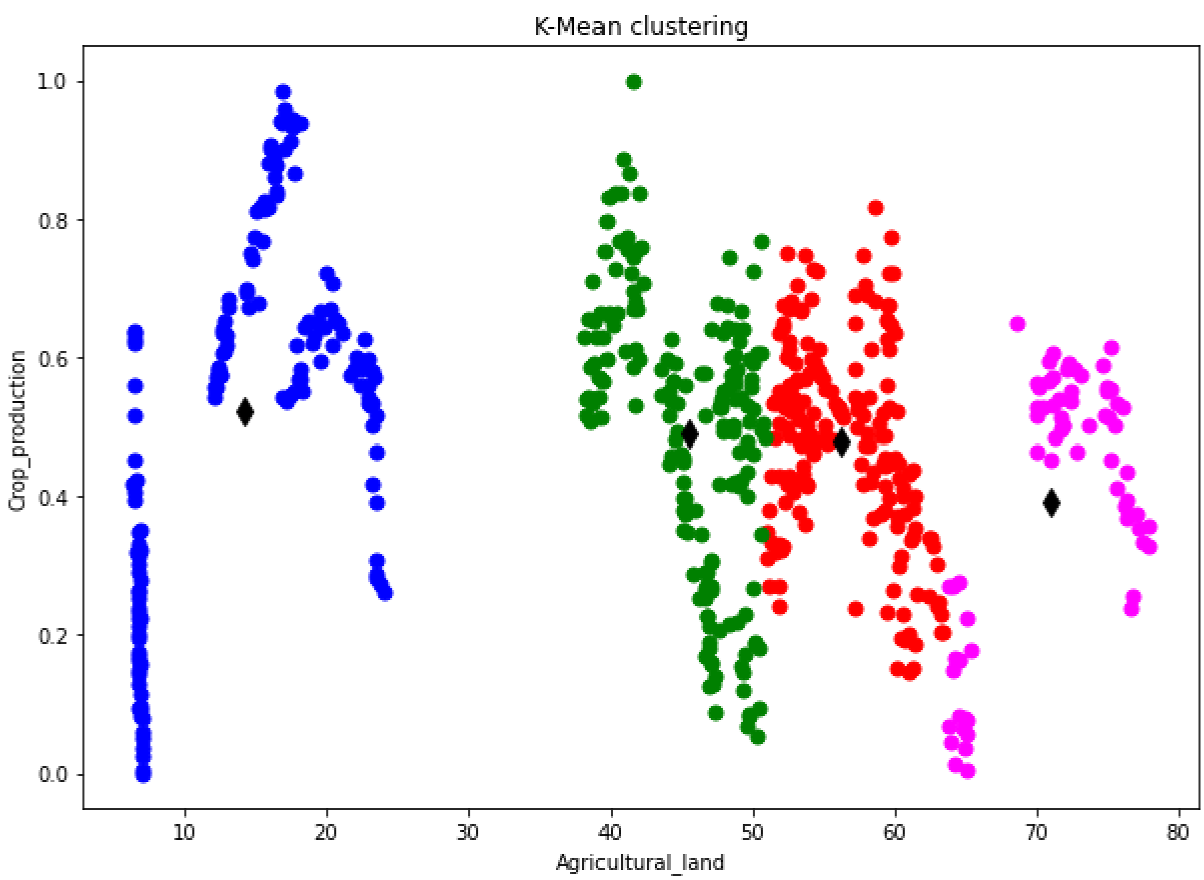





## K Mean Clustering

In [162]:

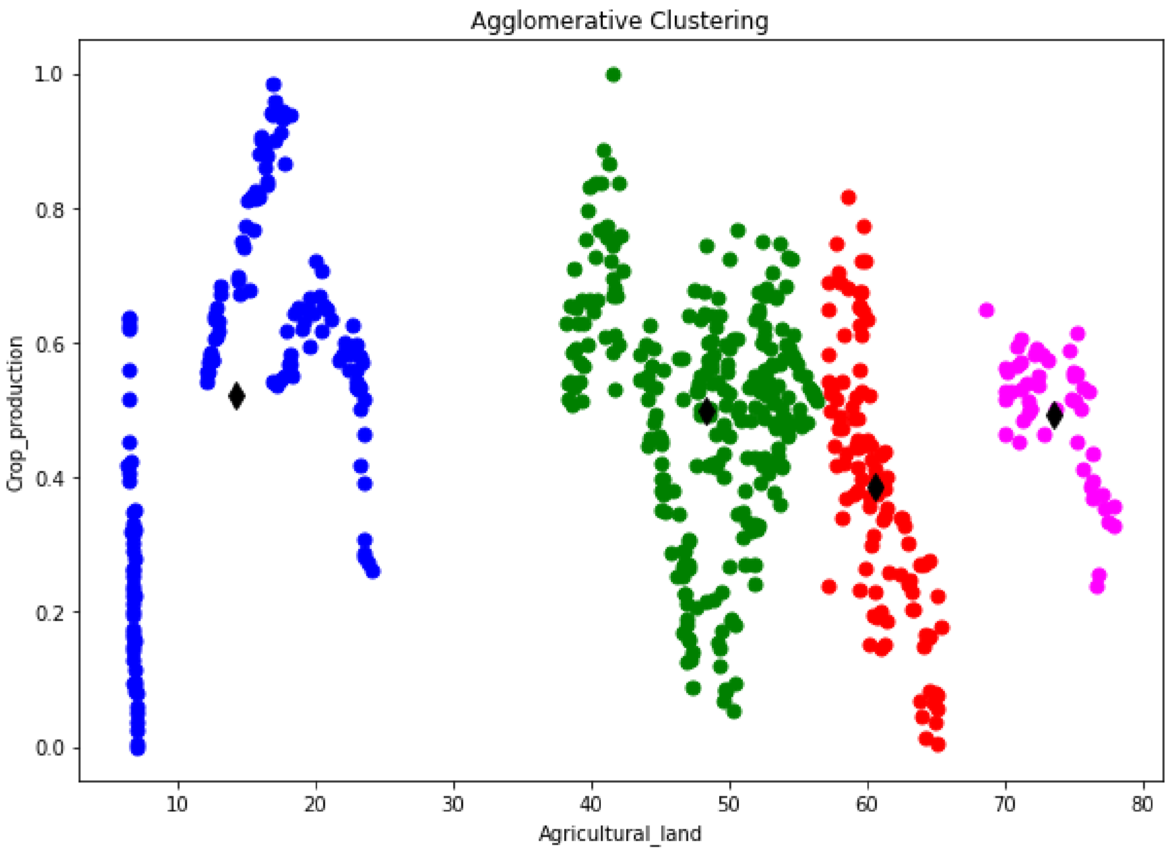
```python
####### kmeans set up the clusterer, 4 expected clusters
kmeans = cluster.KMeans(n_clusters=4)

# extract columns for fitting
df_fit = normalised_df[["Agricultural_land", "Crop_production"]].copy()
kmeans.fit(df_fit)

# extract labels and cluster centres
labels = kmeans.labels_
cen = kmeans.cluster_centers_

# plot using the labels to select colour
plt.figure(figsize=(10.0,7.0))

col = ["blue", "red", "green", "magenta"]
for l in range(4):     # loop over the different labels
    plt.plot(df_fit["Agricultural_land"][labels==l], df_fit["Crop_production"][la
             markersize=7, color=col[l])

# show cluster centres
for ic in range(4):
    xc, yc = cen[ic,:]
    plt.plot(xc, yc, "dk", markersize=10)

plt.xlabel("Agricultural_land")
plt.ylabel("Crop_production")
plt.title('K-Mean clustering')
plt.savefig('K-Mean cluster.jpg')
plt.show()
```



# Agglomerative Clustering

In [163]:

```python
##### setting up agglomerative clustering for 4 clusters
ac = cluster.AgglomerativeClustering(n_clusters=4)

df_fit = normalised_df[["Agricultural_land", "Crop_production"]].copy()

# carry out the fitting
ac.fit(df_fit)

labels = ac.labels_

# The clusterer does not return cluster centres, but they are easily computed
xcen = []
ycen = []
for ic in range(4):
    xc = np.average(df_fit["Agricultural_land"][labels==ic])
    yc = np.average(df_fit["Crop_production"][labels==ic])
    xcen.append(xc)
    ycen.append(yc)

# plot using the labels to select colour
plt.figure(figsize=(10.0,7.0))

col = ["blue", "red", "green", "magenta"]
for l in range(0,4):     # loop over the different labels
    plt.plot(df_fit["Agricultural_land"][labels==l], df_fit["Crop_production"][la
             markersize=7, color=col[l])

# show cluster centres
for ic in range(4):
    plt.plot(xcen[ic], ycen[ic], "dk", markersize=10)

plt.xlabel("Agricultural_land")
plt.ylabel("Crop_production")
plt.title('Agglomerative Clustering')
plt.savefig('agglomerative cluster.jpg')
plt.show()
```




## Data Fitting

In [164]:
```
def exp_growth(t, scale, growth):
    f = scale * np.exp(growth * (t-1990))
    return f


def logistics(t, scale, growth, t0):
    f = scale / (1.0 + np.exp(-growth * (t - t0)))
    return f
# Define the exponential function and the logistics functions for fitting.
```

In [165]:
```
# taking one country from climate set
country_df = bank_data(['AUS'])
country_df
```

```
id              value
--------------  ----------------------------------------
AG.LND.AGRI.ZS  Agricultural land (% of land area)
AG.PRD.CROP.XD  Crop production index (2014-2016 = 100)
AG.PRD.FOOD.XD  Food production index (2014-2016 = 100)
                3 elements

'Checking null values in DataFrame'

Agricultural_land      0
Crop_production        0
Food_production        0
dtype: int64
```

Out[165]:

| Country | Year | Agricultural_land | Crop_production | Food_production |
|---|---|---|---|---|
| **AUS** | **1970** | 64.229788 | 32.430000 | 45.020000 |
| | **1971** | 65.024298 | 35.200001 | 47.450001 |
| | **1972** | 65.060594 | 31.360001 | 48.590000 |
| | **1973** | 64.810929 | 38.509998 | 51.900002 |
| | **1974** | 65.131146 | 37.419998 | 47.040001 |
| | **1975** | 65.025708 | 40.529999 | 51.279999 |
| | **1976** | 65.181261 | 39.980000 | 54.880001 |
| | **1977** | 63.979537 | 36.320000 | 54.270000 |
| | **1978** | 64.577015 | 50.500000 | 62.419998 |
| | **1979** | 64.204470 | 48.619999 | 59.830002 |
| | **1980** | 64.516876 | 40.750000 | 52.590000 |
| | **1981** | 64.507374 | 50.650002 | 56.180000 |
| | **1982** | 63.883472 | 38.790001 | 51.369999 |
| | **1983** | 62.974500 | 60.080002 | 61.290001 |
| | **1984** | 63.334939 | 58.790001 | 58.060001 |
| | **1985** | 63.365268 | 55.450001 | 57.150002 |
| | **1986** | 60.989678 | 55.270000 | 59.099998 |
| | **1987** | 61.312367 | 49.200001 | 58.430000 |
| | **1988** | 61.446702 | 53.459999 | 60.970001 |
| | **1989** | 60.802624 | 54.110001 | 60.020000 |
| | **1990** | 60.455463 | 54.360001 | 62.720001 |
| | **1991** | 60.240032 | 49.119999 | 60.630001 |
| | **1992** | 60.659438 | 58.709999 | 65.760002 |

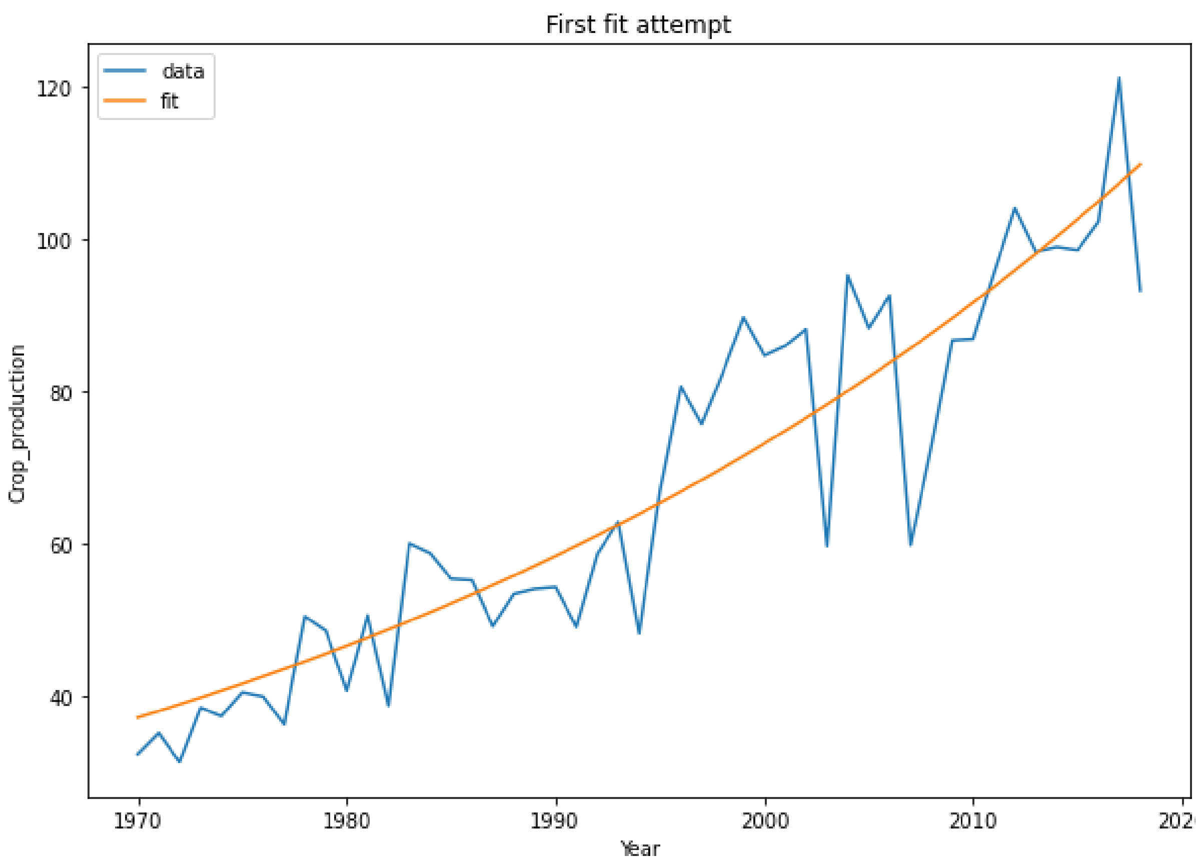
| | | Agricultural_land | Crop_production | Food_production |
|---|---|---|---|---|
| **Country** | **Year** | | | |
| | **1993** | 59.890528 | 62.919998 | 68.480003 |
| | **1994** | 61.068040 | 48.279999 | 63.110001 |
| | **1995** | 60.318915 | 66.940002 | 70.910004 |
| | **1996** | 60.558687 | 80.680000 | 76.370003 |
| | **1997** | 60.168569 | 75.779999 | 75.650002 |
| | **1998** | 60.383088 | 82.419998 | 81.199997 |
| | **1999** | 59.056923 | 89.760002 | 85.820000 |
| | **2000** | 59.288104 | 84.760002 | 84.900002 |
| | **2001** | 59.318173 | 86.040001 | 86.620003 |
| | **2002** | 58.185700 | 88.239998 | 88.169998 |
| | **2003** | 57.209429 | 59.740002 | 72.970001 |
| | **2004** | 51.404657 | 95.300003 | 89.389999 |
| | **2005** | 53.399373 | 88.370003 | 86.709999 |
| | **2006** | 53.278575 | 92.639999 | 90.370003 |
| | **2007** | 51.853677 | 59.869999 | 75.949997 |
| | **2008** | 50.673366 | 72.800003 | 80.370003 |
| | **2009** | 50.018484 | 86.779999 | 86.199997 |
| | **2010** | 48.992099 | 86.940002 | 85.809998 |
| | **2011** | 51.562813 | 95.650002 | 89.769997 |
| | **2012** | 50.385431 | 104.099998 | 94.900002 |
| | **2013** | 48.393710 | 98.379997 | 96.230003 |
| | **2014** | 48.738399 | 99.040001 | 100.029999 |
| | **2015** | 45.314424 | 98.620003 | 100.620003 |
| | **2016** | 44.539926 | 102.330002 | 99.349998 |
| | **2017** | 48.340618 | 121.239998 | 104.040001 |
| | **2018** | 46.658095 | 93.330002 | 94.180000 |

In [166]:
```
ctr=[]
yr=[]
for idx in country_df.index:
    ctr.append(idx[0])
    yr.append(idx[1])
country_df.insert(0,"Country",ctr)
country_df.insert(1,"Year",yr)
country_df=country_df.reset_index(drop=True)
country_df=country_df.fillna(country_df.mean())
country_df["Year"] = country_df["Year"].astype(int)
```

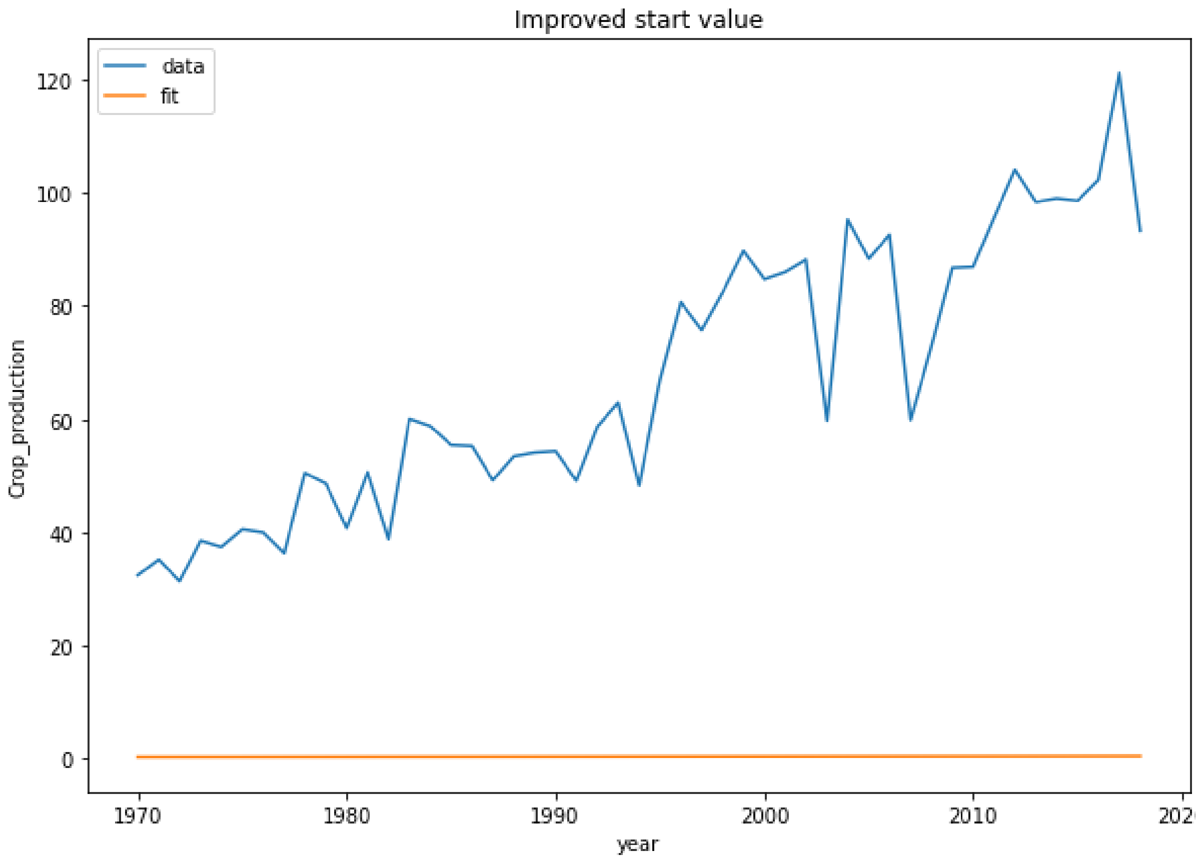
In [167]:
```python
# fit exponential growth
popt, covar = opt.curve_fit(exp_growth, country_df['Year'], country_df['Crop_proc
```

In [168]:
```python
print("Fit parameter", popt)

# use *popt to pass on the fit parameters
country_df["crop_exp"] = exp_growth(country_df["Year"], *popt)

plt.figure(figsize=(10.0,7.0))
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_exp"], label="fit")

plt.legend()
plt.title("First fit attempt")
plt.xlabel("Year")
plt.ylabel("Crop_production")
plt.savefig('exp_first attempt.jpg')
plt.show()
print()
```

```
Fit parameter [5.84383728e+01 2.25371029e-02]
```



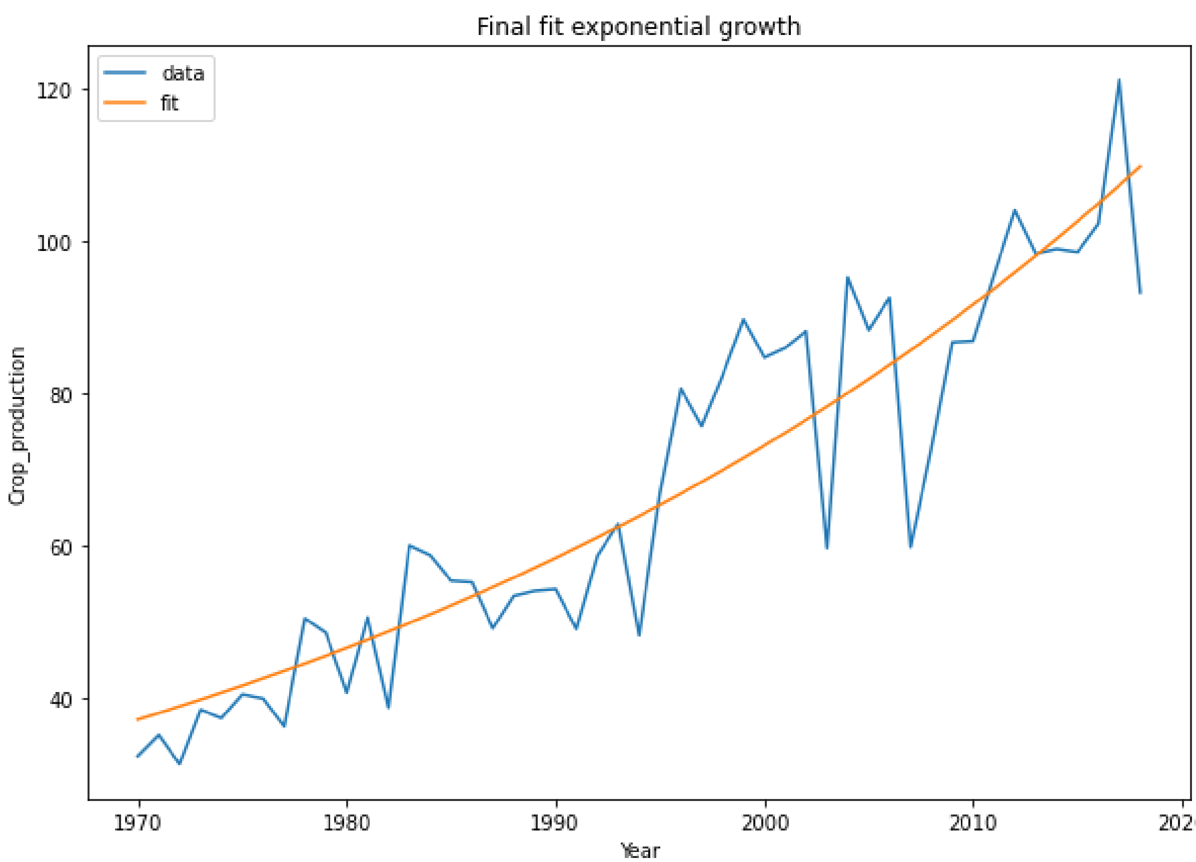
In [169]:
```
# decrease or increase exponential factor until rough agreement is reached
# growth of 0.02 gives a reasonable start value
popt = [0.32, 0.01]
country_df["crop_exp"] = exp_growth(country_df["Year"], *popt)

plt.figure(figsize=(10.0,7.0))
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_exp"], label="fit")

plt.legend()
plt.xlabel("year")
plt.ylabel("Crop_production")
plt.title("Improved start value")
plt.savefig('exp_Improved start.jpg')
plt.show()
```



In [170]:

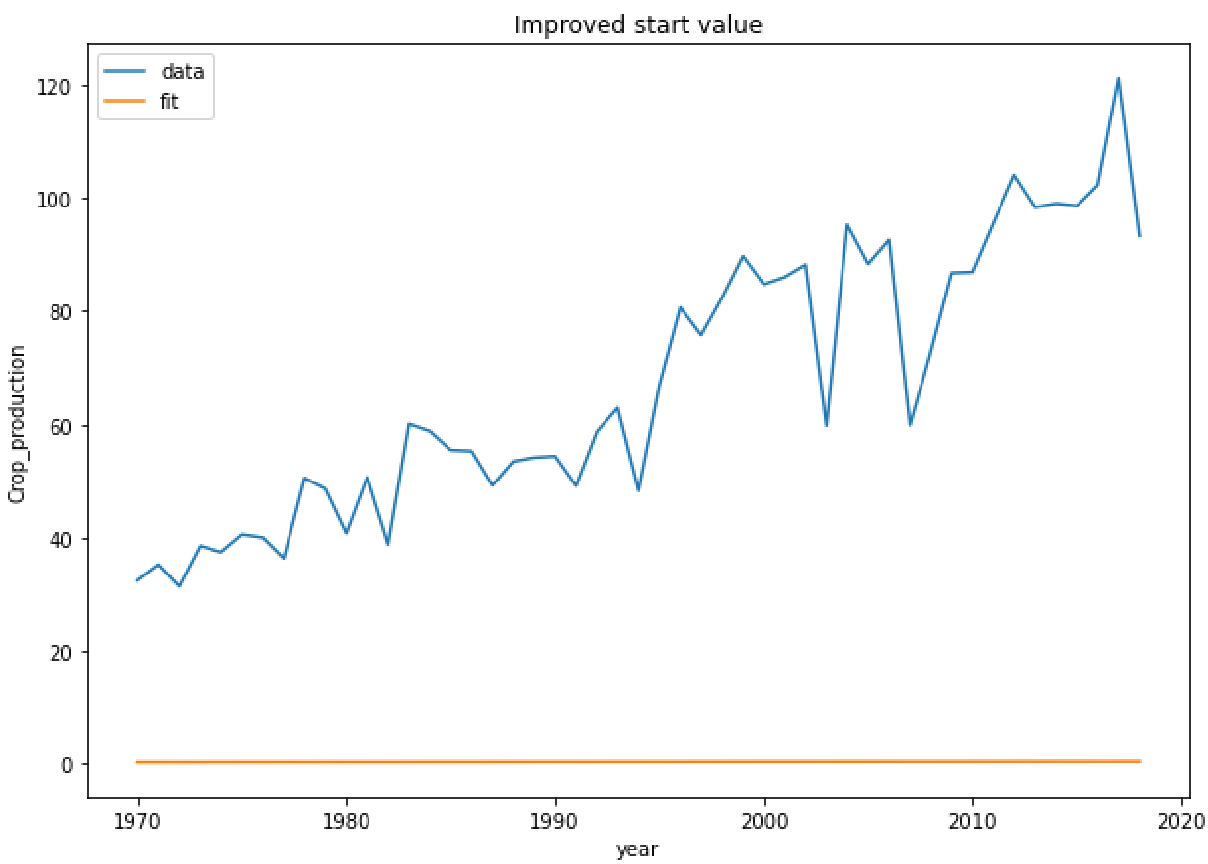
```python
# fit exponential growth
popt, covar = opt.curve_fit(exp_growth, country_df["Year"],
                            country_df["Crop_production"], p0=[0.32, 0.02])
# much better
print("Fit parameter", popt)

country_df["crop_exp"] = exp_growth(country_df["Year"], *popt)

plt.figure(figsize=(10.0,7.0))
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_exp"], label="fit")

plt.legend()
plt.xlabel("Year")
plt.ylabel("Crop_production")
plt.title("Final fit exponential growth")
plt.savefig('exp_final fit.jpg')
plt.show()
print()
```

```
Fit parameter [5.84383657e+01 2.25371127e-02]
```



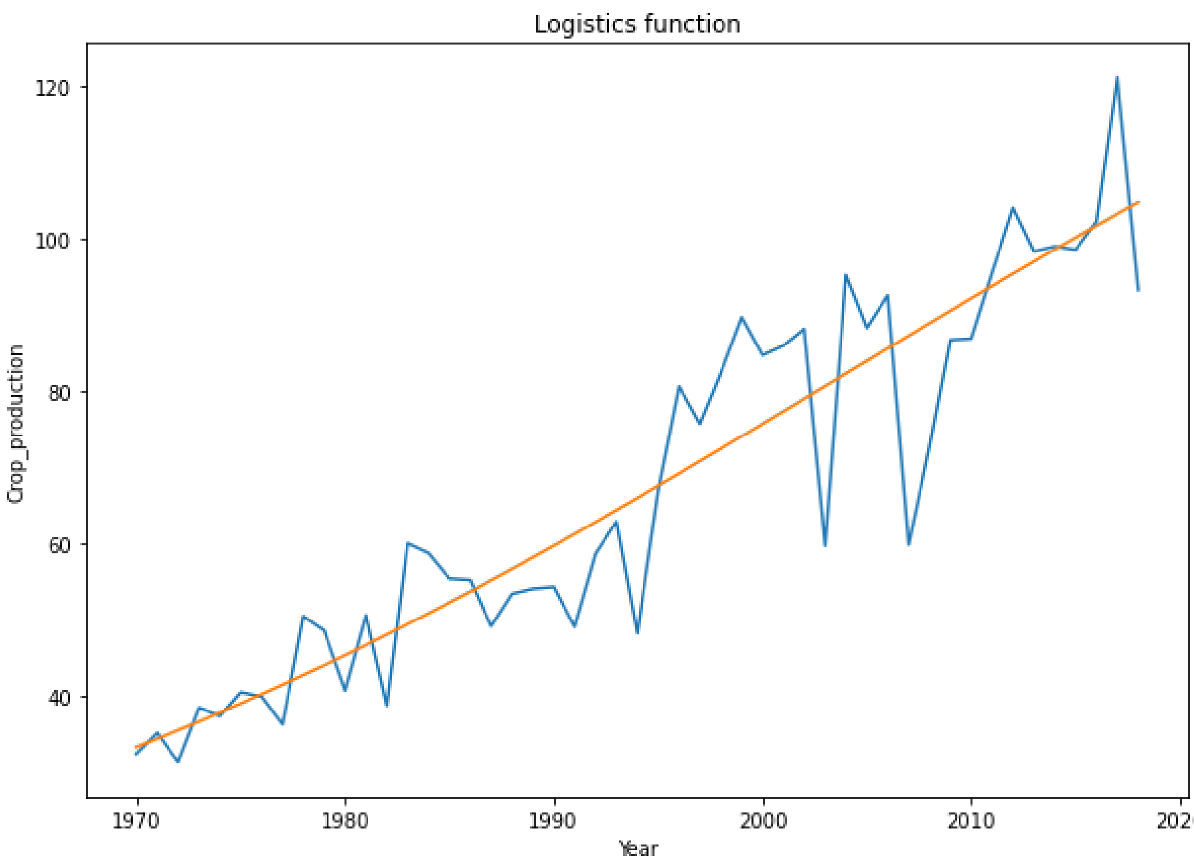
In [171]:

```
# kept growth value from before
# increase scale factor and growth rate until rough fit
popt = [0.54, 0.02, 1990]
country_df["crop_log"] = logistics(country_df["Year"], *popt)

plt.figure(figsize=(10.0,7.0))
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_log"], label="fit")

plt.legend()
plt.xlabel("year")
plt.ylabel("Crop_production")
plt.title("Improved start value")
plt.savefig('log_improved start.jpg')
plt.show()
```



In [187]:
```
popt, covar = opt.curve_fit(logistics, country_df["Year"], country_df["Crop_produ
                            p0=(2e9, 0.05, 1990.0), maxfev=1200)
print("Fit parameter", popt)


country_df["crop_log"] = logistics(country_df["Year"], *popt)

plt.figure(figsize=(10.0,7.0))
plt.title("Logistics function")
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_log"], label="fit")

plt.xlabel("Year")
plt.ylabel("Crop_production")
plt.savefig('log_function.jpg')
plt.show()
```

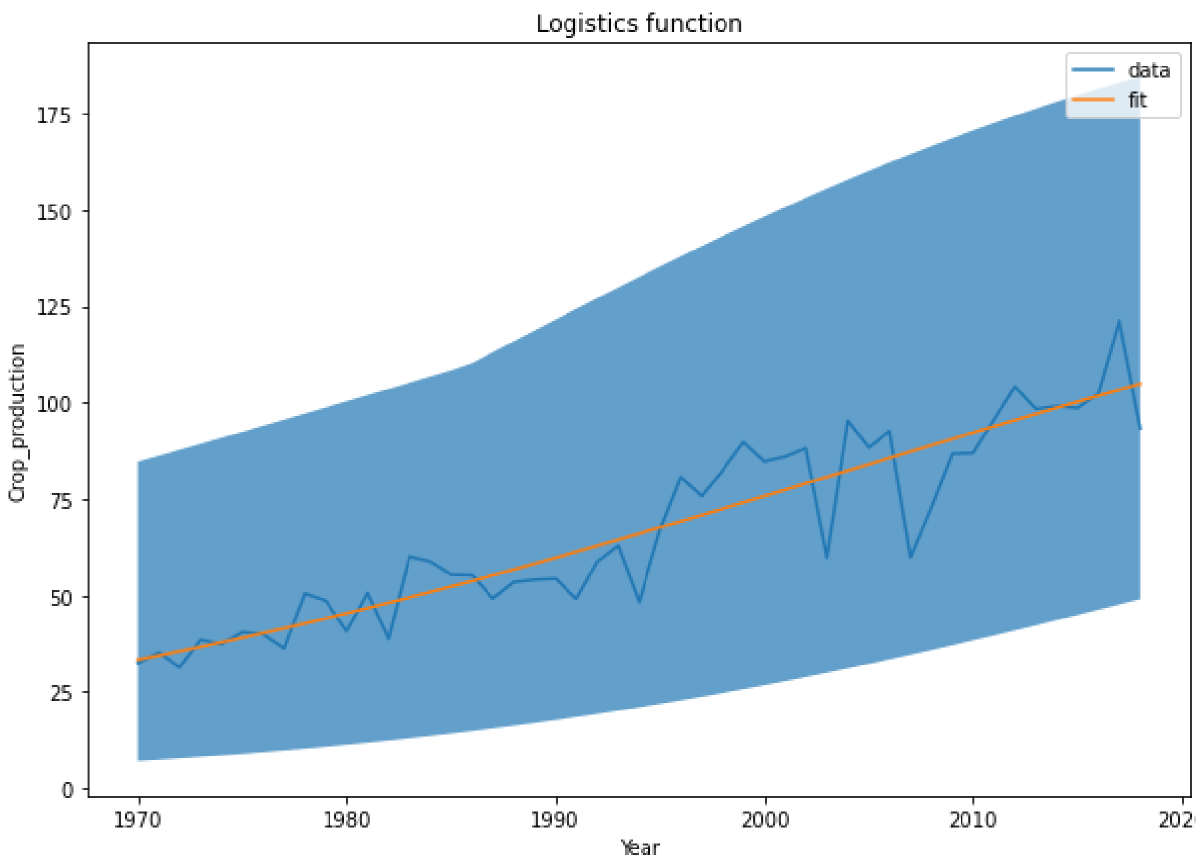
```
Fit parameter [1.63126671e+02 4.05412503e-02 2.00351105e+03]
```



In [188]:

```python
import itertools as iter

def err_ranges(x, func, param, sigma):
    # initiate arrays for lower and upper limits
    lower = func(x, *param)
    upper = lower

    uplow = []   # list to hold upper and lower limits for parameters
    for p,s in zip(param, sigma):
        pmin = p - s
        pmax = p + s
        uplow.append((pmin, pmax))

    pmix = list(iter.product(*uplow))

    for p in pmix:
        y = func(x, *p)
        lower = np.minimum(lower, y)
        upper = np.maximum(upper, y)


    return lower, upper
```

In [189]:
```
# extract the sigmas from the diagonal of the covariance matrix
sigma = np.sqrt(np.diag(covar))

low, up = err_ranges(country_df["Year"], logistics, popt, sigma)

plt.figure(figsize=(10.0,7.0))
plt.title("Logistics function")
plt.plot(country_df["Year"], country_df["Crop_production"], label="data")
plt.plot(country_df["Year"], country_df["crop_log"], label="fit")

plt.fill_between(country_df["Year"], low, up, alpha=0.7)
plt.legend()
plt.xlabel("Year")
plt.ylabel("Crop_production")
plt.savefig('error range.jpg')
plt.show()
```




In [190]:
```
print("Forcasted Crop_production")
low, up = err_ranges(2030, logistics, popt, sigma)
print("2030 between ", low, "and", up)
low, up = err_ranges(2040, logistics, popt, sigma)
print("2040 between ", low, "and", up)
low, up = err_ranges(2050, logistics, popt, sigma)
print("2050 between ", low, "and", up)
```

```
Forcasted Crop_production
2030 between  60.32698741111771 and 199.0963742721422
2040 between  67.83917716206273 and 206.7891088801082
2050 between  74.78712972215187 and 211.66156007700653
```

In [191]:

```
print("Forcasted Crop_production")
low, up = err_ranges(2030, logistics, popt, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2030:", mean, "+/-", pm)

low, up = err_ranges(2040, logistics, popt, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2040:", mean, "+/-", pm)

low, up = err_ranges(2050, logistics, popt, sigma)
mean = (up+low) / 2.0
pm = (up-low) / 2.0
print("2050:", mean, "+/-", pm)
```

```
Forcasted Crop_production
2030: 129.71168084162997 +/- 69.38469343051224
2040: 137.31414302108544 +/- 69.47496585902273
2050: 143.2243448995792 +/- 68.43721517742733
```

In [ ]:

```
```