Classify BC BGC zones by Koppen-Geiger

We're using a Jupyter Notebook with Python (programming language) and Pandas (data science framework) to classify British Columbia's BioGeoClimatic zones by the Koppen-Geiger global classification system.

This should help understand which global species may be interested in invading specific areas of BC.

In [1]:
```
import pandas as pd
```

Pull in the data

Let's open the BioGeoClimatic zone data as a Pandas DataFrame object. The data has been rescued from Microsoft Access via a table export and is in the working directory as a comma-delimited text file called `BGC_Units.txt` .

In [2]:
```
df = pd.read_csv('BGC_Units.txt')
# While we're at it, we'll check how many rows are in the dataset.
print(f'There are {len(df)} rows in the dataset.')
```

```
There are 11872 rows in the dataset.
```

The explanations (helpstrings) of the cryptic column names are in a CSV file called `tblTasksFields.csv` (which needed a bit of extra massaging after rescuing from MSAccess to remove non-compliant Unicode degree symbols).

In [3]:
```
hs = pd.read_csv('tblTasksFields.csv')
```

Let's make a dictionary with the column names as the keys and the description helpstrings as the values. We've manually identified column 2 as containing the zone/subzone/variant id string and column 5 as containing the explanatory helpstring.

In [4]:
```
colnames = {}
for item in hs.itertuples():
    colnames[item[2]] = item[5]
```

Let's look at all of the column headers, the type of each column (Pandas infers a datatype *for an entire column* based on the values it finds in them), and the explanatory helpstrings.

In [5]:
```
cols = [[x[0], x[1], colnames.get(x[0])]
        for x in zip(df.columns, df.dtypes)]
# Print first 25 columns to get a sense of the schema
for name in cols[:25]:
    print(name)
```

```
['ID', dtype('int64'), None]
['BGC', dtype('O'), None]
['period', dtype('O'), None]
['Var', dtype('O'), None]
['Tmax01', dtype('float64'), 'Temperature max']
['Tmax02', dtype('float64'), 'Temperature max']
['Tmax03', dtype('float64'), 'Temperature max']
['Tmax04', dtype('float64'), 'Temperature max']
['Tmax05', dtype('float64'), 'Temperature max']
['Tmax06', dtype('float64'), 'Temperature max']
['Tmax07', dtype('float64'), 'Temperature max']
['Tmax08', dtype('float64'), 'Temperature max']
['Tmax09', dtype('float64'), 'Temperature max']
['Tmax10', dtype('float64'), 'Temperature max']
['Tmax11', dtype('float64'), 'Temperature max']
['Tmax12', dtype('float64'), 'Temperature max']
['Tmin01', dtype('float64'), 'Temperature min']
['Tmin02', dtype('float64'), 'Temperature min']
['Tmin03', dtype('float64'), 'Temperature min']
['Tmin04', dtype('float64'), 'Temperature min']
['Tmin05', dtype('float64'), 'Temperature min']
['Tmin06', dtype('float64'), 'Temperature min']
['Tmin07', dtype('float64'), 'Temperature min']
['Tmin08', dtype('float64'), 'Temperature min']
['Tmin09', dtype('float64'), 'Temperature min']
```

Ok, the first column is an incrementing ID, the following three columns are objects (well, strings). The remaining columns are all numbers, mostly floating-point decimals with a few integers here and there. Note that many seem to consist of a string like `Tmax` followed by a

number between `01` and `12`; these represent months.

Let's grab the three string columns and see how many unique values they contain, and what they are. From the previous cell's output, we know that the first is a zone/subzone/variant ID string, the second a range from a start to end year, and the third describes the statistical operation that's generated the actual values in the row.

A Python set will allow us to look at only the unique values, so we can see all of the different zones, date ranges, and statistical operations that the values come from.

In [6]:
```
dateranges = set()
bgczones = set()
vardefs = set()
for row in df.itertuples():
    bgczones.add(row[2])
    dateranges.add(row[3])
    vardefs.add(row[4])
```

Let's look at all of the unique date ranges, statistical outputs, and zone/subzone/variant identifiers in the data:

In [7]:
```
print(f'There are {len(dateranges)} unique date '\
      f'ranges:\n{dateranges}')
print(f'\nThere are {len(vardefs)} unique statistical '\
      f'operations the values come from: \n{vardefs}')
print(f'\nThere are {len(bgczones)}  unique zone/subzone'\
      f'/variants: \n{bgczones}')
```

```
There are 8 unique date ranges:
{'1961-1990', '1990-2014', '1977-1998', '1901-1990', '1945-1976', '1901-1960', '1971-2000', '1901-2014'}

There are 7 unique statistical operations the values come from:
{'mean', '95%', 'max', 'min', 'st.dev.Ann', 'st.dev.Geo', '5%'}

There are 212  unique zone/subzone/variants:
{'BWBSwk 1', 'ESSFmkp', 'ESSFdh 2', 'ESSFmw 1', 'CWH ws 2', 'CWH wh 1', 'SBS dw 1', 'BG  xw 1', 'BWBSmw', 'IDF
dk 5', 'ICH dw 3', 'MH  whp', 'SBS mc 1', 'ESSFmv 1', 'CWH vh 2', 'ESSFdcp', 'ESSFmw', 'ESSFxvp', 'IDF ww', 'MH
mm 1', 'MH  mmp', 'ESSFun', 'MS  dc 1', 'MS  xv', 'CMA wh', 'SBS un', 'CWH vm 1', 'MS  dv', 'CWH xm 2', 'ESSFdc
1', 'ESSFwc 3', 'BWBSvk', 'ESSFwh 3', 'IDF ww 1', 'IDF xk', 'SBS vk', 'SBS mm', 'CWH wm', 'CWH un', 'ESSFdkp',
'SBS dw 2', 'ICH xw', 'ESSFmc', 'CWH mm 1', 'MH  un', 'ICH mk 1', 'CWH ws 1', 'IMA unp', 'ICH mk 4', 'IDF xc',
'MS  dm 3', 'SBPSmc', 'SBS wk 3', 'CWH vm 1N', 'MS  dc 3', 'ICH mm', 'IDF dh', 'ESSFxvw', 'ESSFxv 2', 'MS  dm
2', 'CWH ds 2', 'ICH vc', 'IDF dm 2', 'ESSFwcw', 'ICH wc', 'MS  dm 1', 'IDF dk 2', 'ESSFxcp', 'ESSFxv 1', 'SBS
mh', 'ICH mw 2', 'SBS mk 2', 'SBS mc 2', 'ESSFdk 1', 'ESSFdvw', 'IDF mw 1', 'SBS dw 3', 'IDF xx 1', 'ICH mc 2',
'SBPSdc', 'ICH wk 1', 'CMA un', 'ESSFmw 2', 'ESSFwmp', 'BAFAun', 'ESSFxc 2', 'SBPSmk', 'ESSFmcp', 'ESSFvk', 'ES
SFdh 1', 'ESSFdc 2', 'ESSFvcp', 'ESSFvc', 'CWH xm 1', 'MS  dk', 'ESSFwk 1', 'CWH wh 2', 'IDF dc', 'IDF xh 2',
'MH  unp', 'ESSFmh', 'BWBSdk', 'CDF mm', 'ICH mk 5', 'CWH mm 2', 'ESSFwc 4', 'ESSFxc 3', 'IDF mw 2', 'BG  xh
2', 'IDF xm', 'MH  wh', 'ESSFwc 2', 'SBS wk 2', 'BG  xh 1', 'ESSFwh 2', 'SBS dk', 'CWH ms 1', 'ESSFwm 4', 'IMA
un', 'ESSFvm', 'PP  xh 1', 'IDF dk 3', 'ESSFdvp', 'ESSFvcw', 'ICH wk 3', 'ESSFmmp', 'ICH mc 1', 'ICH mk 3', 'CW
H ds 1', 'ESSFwh 1', 'MH  wh 1', 'IDF xh 1', 'ESSFdkw', 'PP  xh 2', 'ESSFmv 4', 'SBPSxc', 'SWB mks', 'SWB vks',
'ESSFunp', 'MH  mm 2', 'CWH dm', 'ICH mw 6', 'ESSFwvp', 'SBS dh 1', 'ICH mw 1', 'ICH mk 2', 'ESSFdk 2', 'CMA un
p', 'ICH dw 1', 'ESSFwv', 'IDF xx 2', 'BWBSwk 2', 'ESSFdv 1', 'ESSFmm 2', 'ESSFwmw', 'ESSFwm 1', 'ESSFmk', 'IDF
dk 1', 'MS  xk 2', 'ICH vk 1', 'ICH dm', 'ESSFmm 1', 'MS  dw', 'ESSFwcp', 'MS  xk 3', 'IDF dw', 'ESSFmmw', 'ESS
Fmv 2', 'SWB uns', 'ESSFdv 2', 'ESSFdcw', 'SBS wk 1', 'ESSFmww', 'MS  xk 1', 'ICH mw 4', 'SBS dh 2', 'ESSFmvp',
'ESSFmwp', 'SBS mc 3', 'BWBSwk 3', 'ESSFdc 3', 'CWH ms 2', 'MS  dc 2', 'ESSFwm 2', 'PP  xw', 'ESSFxcw', 'BG  xw
2', 'ICH mw 3', 'ICH wk 4', 'ICH wk 2', 'IDF dk 4', 'SBS mk 1', 'SBS mw', 'BAFAunp', 'ESSFwm 3', 'SWB un', 'SWB
vk', 'MS  un', 'BWBSmk', 'CWH vm 2', 'ICH vk 2', 'ICH mw 5', 'CWH vh 1', 'ICH dk', 'IDF dm 1', 'BG  xh 3', 'SWB
mk', 'ESSFwk 2', 'CWH vh 3', 'IDF xw', 'ESSFxc 1', 'ESSFmv 3'}
```

Right! For the moment, we only want to consider the date range from 1961 to 1990, though perhaps in the future someone might want to consider different ranges, so it's nice that we have them just in case.

Furthermore, we only want to use the mean values to key out the Koppen-Geiger classes of the zone/subzone/variants. Someone smarter than us may later wish to do a more sophisticated classification, but not today.

So we're only going to using a small subset of the data to classify the zone/subzone/variants. Let's create that subset now with a filter.

In [8]:
```
# create a filtered DataFrame (call it fdf)
fdf = df[(df['period']=='1961-1990') & (df['Var']=='mean')]
fdf
```

Out[8]:

	ID	BGC	period	Var	Tmax01	Tmax02	Tmax03	Tmax04	Tmax05	Tmax06	...	bFFP	eFFP	FFP	PAS	EMT	E
3	4	BAFAun	1961-1990	mean	-8.86	-6.50	-4.46	0.18	5.57	9.68	...	180.59	228.16	47.58	1005.53	-44.43	24
87	88	BAFAunp	1961-1990	mean	-4.83	-1.79	0.40	3.34	8.12	11.64	...	182.28	238.45	56.16	1044.44	-41.48	27

	ID	BGC	period	Var	Tmax01	Tmax02	Tmax03	Tmax04	Tmax05	Tmax06	...	bFFP	eFFP	FFP	PAS	EMT	E
143	144	BG xh 1	1961-1990	mean	0.04	4.46	10.50	16.06	21.03	25.30	...	113.32	287.28	173.96	46.62	-29.82	39
199	200	BG xh 2	1961-1990	mean	-1.89	2.95	9.33	15.24	20.21	24.47	...	123.88	278.51	154.61	65.00	-33.37	37
255	256	BG xh 3	1961-1990	mean	-2.78	2.55	8.77	14.54	19.48	23.69	...	131.22	273.63	142.39	74.45	-34.92	37
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11623	11624	SWB mks	1961-1990	mean	-8.69	-5.73	-3.41	2.53	7.96	12.13	...	180.82	233.45	52.63	495.86	-44.37	26
11679	11680	SWB un	1961-1990	mean	-10.73	-6.33	-2.07	3.68	9.38	14.21	...	176.09	235.97	59.87	375.10	-45.50	28
11735	11736	SWB uns	1961-1990	mean	-10.08	-6.26	-3.08	2.10	7.91	12.57	...	178.06	232.03	53.96	455.28	-45.51	26
11791	11792	SWB vk	1961-1990	mean	-6.95	-3.82	-0.41	4.32	9.35	13.08	...	161.33	251.51	90.16	1394.19	-37.62	27
11847	11848	SWB vks	1961-1990	mean	-8.63	-5.42	-2.11	2.80	7.92	11.72	...	174.74	240.86	66.13	2292.16	-40.00	26

212 rows × 251 columns

Nice! Not only is this a much smaller dataset, we can see that it has the same number of rows as there are unique zone/subzone/variants. That's a good sanity check on the filter as well as a bit of reassurance regarding the quality of the dataset.

Using Koppen-Geiger key to build a classifier

Let's build a function that accepts a row from the dataset as input, and returns a Koppen-Geiger class string if it matches the parameters, or `None` if not.

First we'll need some helper functions!

Some helper functions

Most of the Koppen-Geiger criteria involve finding minimum and maximum temperature and/or precipitation values across multiple months. For example, the average temperature is found in the dataset in columns with headers labelled `Tave01` `Tave02` ... `Tave12` for January through December. So we'll create a helper function (twelvemonther) to generate those column names so we can use them as keys to extract the appropriate series.

Additionally, the algorithm often wants to compare winter and/or summer maxima and minima (with summer defined as April-September and winter defined as . So we'll create two more helper functions (summer and winter) to generate those column names.

In [9]:
```
def twelvemonther(s):
    """Creates a list with 01 to 12 appended to a given string"""
    return [f'{s}{str(x + 1).zfill(2)}' for x in range(12)]

def summer(s):
    """Creates a list with 04 to 09 appended to a given string
    because summer is defined as April-September in K-G."""
    return [f'{s}{str(x + 1).zfill(2)}' for x in range(3,9)]

def winter(s):
    """Creates a list with 01 to 03 and 10 to 12 appended to a given
    string because winter is defined as October-March in K-G."""
    jan_mar = [f'{s}{str(x + 1).zfill(2)}' for x in range(3)]
    oct_dec = [f'{s}{str(x + 1).zfill(2)}' for x in range(9,12)]
    return jan_mar + oct_dec
```

First, second, and third letter functions

Now we'll create some functions for each of the three letters in the Koppen-Geiger system. The rug that ties the room together will come after we sort out the individual letters based on the rules in the key algorithm (which we've copied into comments in the code).

The first letter

In [10]:

```
def first(m, y):
    """returns first letter of the Koppen-Geiger classification"""
    # A
    # Temperature of coolest month 18 degrees Celsius or higher
    if min(m['tave']) >= 18:
        return 'A'

    # B2
    # **(why is it B2? Where is B1? Or plain old B?)**
    # 70% or more of annual precipitation falls in the summer half
    # of the year and r less than 20t + 280, or 70% or more of annual
    # precipitation falls in the winter half of the year and r less
    # than 20t, or neither half of the year has 70% or more of annual
    # precipitation and r less than 20t + 1403"""

    # C
    # Temperature of warmest month greater than or equal to
    # 10 degrees Celsius, and temperature of coldest month
    # less than 18 degrees Celsius but greater than –3 degrees
    # Celsius"""
    if max(m['tave']) >= 10 and -3 < min(m['tave']) < 19:
        return 'C'

    # D
    # Temperature of warmest month greater than or equal to
    # 10 degrees Celsius, and temperature of coldest month
    # –3 degrees Celsius or lower
    if max(m['tave']) >= 10 and min(m['tave']) < -3:
        return 'D'

    # E
    # Temperature of warmest month less than 10 degrees Celsius
    if min(m['tave']) < 10:
        return 'E'

    # A through E all failed to return anything
    return ''
```

The second letter

In [11]:

```
def c_d_second(m, y):
    """returns second letter of the Koppen-Geiger classification
    in the cases that the first letter is C or D"""
    # s
    # Precipitation in driest month of summer half of the year is
    # less than 30 mm and less than one-third of the wettest month
    # of the winter half"""
    dmsp = min(m['summerppt'])
    if (dmsp < 30 and dmsp < (max(m['winterppt'])/3)):
        return 's'

    # w
    # Precipitation in driest month of the winter half of the year
    # less than one-tenth of the amount in the wettest month of
    # the summer half
    elif min(m['winterppt']) < (max(m['summerppt'])/10):
        return 'w'

    # s and w failed to return anything
    else:
        return 'f'

def e_second(m, y):
    # T
    # Temperature of warmest month greater than 0 degrees Celsius
    # but less than 10 degrees Celsius
    if 0 < max(m['tave']) < 10:
        return 'T'

    # F
    # Temperature of warmest month 0 degrees Celsius or below
    elif max(['tave']) <= 0:
        return 'F'
    else:
        return ''
```

The third letter

In [12]:
```
def c_d_third(m, y):
    """returns third letter of the Koppen-Geiger classification
    in the cases that the first letter is C or D"""
    # d
    # Temperature of coldest month less than –38 degrees Celsius
    # (d designation then used instead of a, b, or c)
    if min(m['tave']) < -38: # that's really unpleasantly cold
        return 'd'

    # a
    # Temperature of warmest month 22 degrees Celsius or above
    elif max(m['tave']) >= 22:
        return 'a'

    # b
    # Temperature of each of four warmest months 10 degrees Celsius
    # or above but warmest month less than 22 degrees Celsius
    elif all([x >= 10 for x in sorted(m['tave'], reverse=True)[:4]]):
        return 'b'

    # c
    # Temperature of one to three months 10 degrees Celsius or above
    # but warmest month less than 22 degrees Celsius
    elif max(m['tave']) >= 10:
        return 'c'

    return ''
```

At long last: the actual classification function!

Now that we have the helpers and the functions to return the three different letters, let's put it together.

We start by using our helper functions to grab 12-month series of temperature and precipitation data, as well as the yearly average temp and precip. Then we call the letter functions using the "monthlies" and "yearlies" as input.

In [13]:
```
def kg(zsv):
    """Classify a zone/subzone/variant to a Koppen-Geiger type."""
    monthlies = {
        'tave': [zsv[i] for i in twelvemonther('Tave')],
        'summertave': [zsv[i] for i in summer('Tave')],
        'wintertave': [zsv[i] for i in winter('Tave')],
        'ppt': [zsv[i] for i in twelvemonther('PPT')],
        'summerppt': [zsv[i] for i in summer('PPT')],
        'winterppt': [zsv[i] for i in winter('PPT')],
    }

    # TODO: blank, fetch if needed
    yearlies = {
        't': [], #average annual temperature in deg C
        'r': [], #average annual precipitation in mm
    }

    #print(f"Temperatures: {monthlies['tave']}")
    #print(f"Precipitation: {monthlies['ppt']}")

    l1 = first(monthlies, yearlies)
    if (l1 == 'C' or l1 == 'D'):
        l2 = c_d_second(monthlies, yearlies)
    elif l1 == 'E':
        l2 = e_second(monthlies, yearlies)
    else:
        l2 = ''

    l3 = c_d_third(monthlies, yearlies)

    return l1 + l2 + l3
```

Ok, let's iterate through all of the filtered zone/subzone/variants and see what our function spits out (only printing the first 15 lines to avoid many pages of output).

In [14]:
```
classification = [(row[1][1], kg(row[1])) for row in fdf.iterrows()]
```

```
classification[:15]
```

Out[14]:
```
[('BAFAun', 'ET'),
 ('BAFAunp', 'ET'),
 ('BG  xh 1', 'Cfb'),
 ('BG  xh 2', 'Dfb'),
 ('BG  xh 3', 'Dfb'),
 ('BG  xw 1', 'Dfb'),
 ('BG  xw 2', 'Dfb'),
 ('BWBSdk', 'Dsc'),
 ('BWBSmk', 'Dfc'),
 ('BWBSmw', 'Dfc'),
 ('BWBSvk', 'Dfc'),
 ('BWBSwk 1', 'Dfc'),
 ('BWBSwk 2', 'Dfc'),
 ('BWBSwk 3', 'Dfc'),
 ('CDF mm', 'Csb')]
```

Map it and see if it matches other maps

Now we can add the Koppen-Geiger classification strings as attributes to a GIS file and create a categorized map.

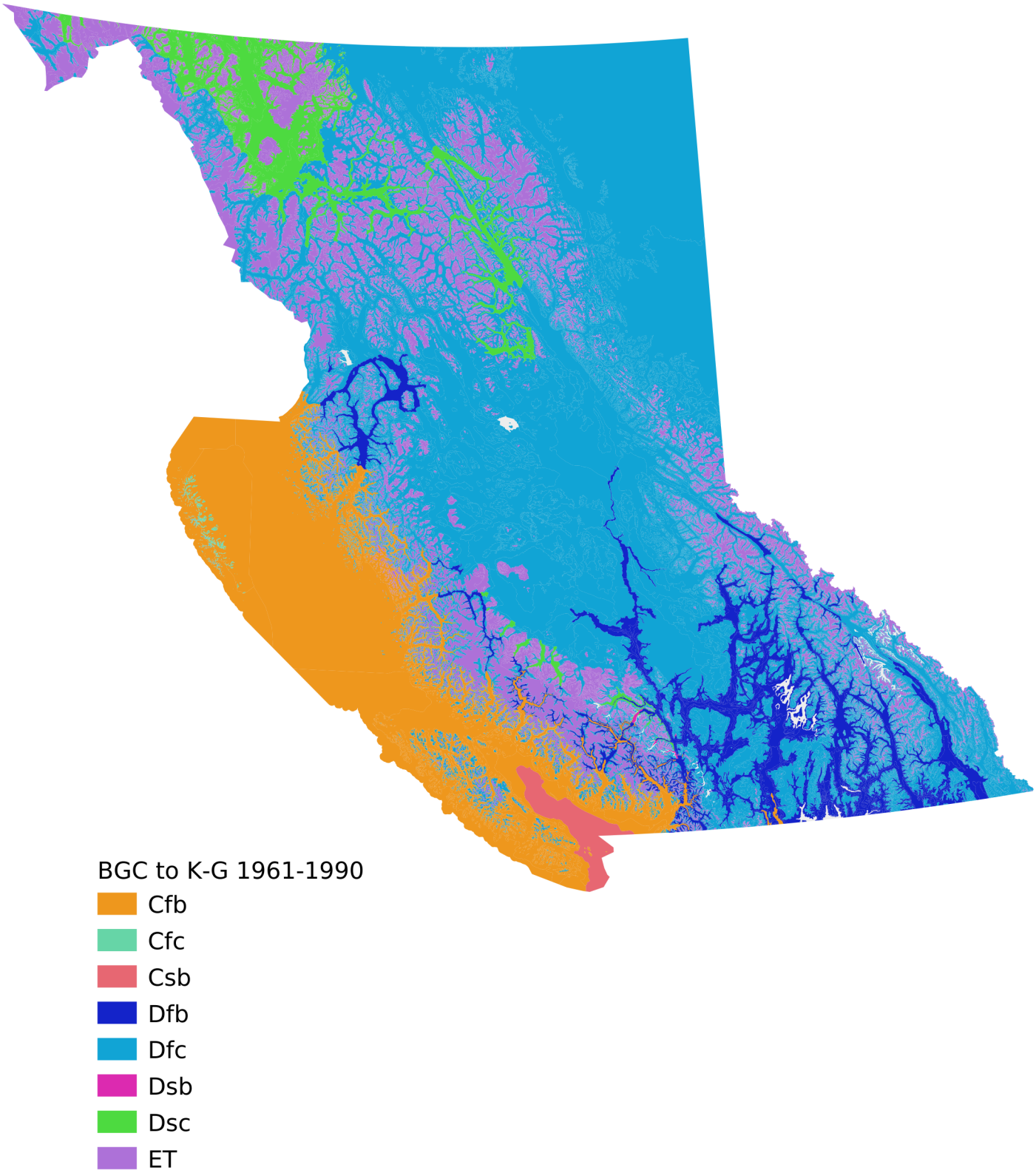
We can compare that map to others generated on a global scale using the K-G categories; we would expect that they should roughly match, but the categorization generated from the BGC data should be much higher resolution and more accurate as it's derived from much more detailed data than the global dataset could possibly be.

First let's export a Comma Separated Values file (.csv) with the BGC labels in one column and the K-G classifications in the other.

In [15]:
```
import csv
with open('bec_2_k-g.csv','w') as f:
    w = csv.writer(f)

    # header row
    w.writerow(['BGC', 'KG'])
    # data rows
    for row in classification:
        w.writerow(row)
```

Now we cheat, and load that CSV file into QGIS along with the `BEC_BIOGEOCLIMATIC_POLY` file from the BC government GIS portal (it would be better to do the mapping right here in the Jupyter notebook to make the whole project more self-contained, but it's faster to start using QGIS).

The next two pages are maps exported from QGIS with the Koppen-Geiger classifications color-coded (randomly; we should probably try to match the colors to some global K-G maps, but for now we just want to see the results to check if they make sense at first blush).


BGC to K-G 1961-1990
Cfb
Cfc
Csb
Dfb
Dfc
Dsb
Dsc
ET

More recent climate data

Now that we've built all of the scaffolding to classify BGC zone/subzone/variants by Koppen-Geiger, we can experiment easily. What would happen if we used the most recent data from ClimateBC, the series from 1990-2014? Let's find out.

In [16]:
```
# Filter the original DataFrame for 1990-2014
fdf2014 = df[(df['period']=='1990-2014') & (df['Var']=='mean')]
fdf2014
```

Out[16]:

	ID	BGC	period	Var	Tmax01	Tmax02	Tmax03	Tmax04	Tmax05	Tmax06	...	bFFP	eFFP	FFP	PAS	EMT	E
52	53	BAFAun	1990-2014	mean	-7.36	-5.52	-4.26	1.09	6.40	10.34	...	181.45	232.76	51.31	976.48	-44.43	24
108	109	BAFAunp	1990-2014	mean	-3.40	-1.54	0.47	3.97	8.69	11.94	...	180.46	241.06	60.59	1003.45	-41.48	27
164	165	BG xh 1	1990-2014	mean	1.21	4.56	10.74	16.16	21.27	24.67	...	108.32	291.53	183.20	36.61	-29.82	39
220	221	BG xh 2	1990-2014	mean	-0.25	3.41	9.66	15.49	20.49	24.09	...	119.11	281.01	161.89	52.15	-33.37	37
276	277	BG xh 3	1990-2014	mean	-1.14	2.99	9.07	15.03	20.00	23.64	...	128.68	274.69	146.01	63.05	-34.92	37
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
11644	11645	SWB mks	1990-2014	mean	-7.38	-4.60	-3.17	3.46	8.74	12.79	...	180.82	237.91	57.09	480.05	-44.37	26
11700	11701	SWB un	1990-2014	mean	-9.26	-5.37	-2.05	4.75	10.50	15.20	...	173.31	240.92	67.63	367.05	-45.50	28
11756	11757	SWB uns	1990-2014	mean	-8.45	-5.29	-3.09	3.21	9.03	13.57	...	175.76	237.59	61.82	446.18	-45.51	26
11812	11813	SWB vk	1990-2014	mean	-5.07	-2.70	-0.12	5.53	10.74	14.21	...	157.79	256.35	98.57	1327.76	-37.62	27
11868	11869	SWB vks	1990-2014	mean	-6.76	-4.31	-1.81	4.01	9.29	12.85	...	171.90	246.25	74.34	2203.05	-40.00	26

212 rows × 251 columns

Same number of rows. Good news there; we don't want to be classifying zones by an incomplete set of climate numbers.

Ok, let's run this series through our classification function. Any differences? Let's create a comparison and look at them side-by-side (again only 15 lines).

In [17]:
```
c2014 = [(row[1][1], kg(row[1])) for row in fdf2014.iterrows()]

# N.B. this zip is risky; if the datasets are not identically
# ordered something bad will happen. Should improve this with
# a dictionary lookup instead of 2-list zip. For now it works,
# as long as we check that BGC labels are the same in each row.
comp = [row for row in zip(classification, c2014)]
comp[:15]
```

Out[17]:
```
[(('BAFAun', 'ET'), ('BAFAun', 'ET')),
 (('BAFAunp', 'ET'), ('BAFAunp', 'ET')),
 (('BG  xh 1', 'Cfb'), ('BG  xh 1', 'Cfa')),
 (('BG  xh 2', 'Dfb'), ('BG  xh 2', 'Dfb')),
 (('BG  xh 3', 'Dfb'), ('BG  xh 3', 'Dfb')),
 (('BG  xw 1', 'Dfb'), ('BG  xw 1', 'Dfb')),
 (('BG  xw 2', 'Dfb'), ('BG  xw 2', 'Dfb')),
 (('BWBSdk', 'Dsc'), ('BWBSdk', 'Dfc')),
 (('BWBSmk', 'Dfc'), ('BWBSmk', 'Dfc')),
 (('BWBSmw', 'Dfc'), ('BWBSmw', 'Dfc')),
 (('BWBSvk', 'Dfc'), ('BWBSvk', 'Dfc')),
 (('BWBSwk 1', 'Dfc'), ('BWBSwk 1', 'Dfc')),
 (('BWBSwk 2', 'Dfc'), ('BWBSwk 2', 'Dfc')),
 (('BWBSwk 3', 'Dfc'), ('BWBSwk 3', 'Dfc')),
 (('CDF mm', 'Csb'), ('CDF mm', 'Csb'))]
```

Yes, there are a few differences! Let's isolate and count them.

In [18]:

```
diff1990_2014 = [(row[0][0], row[0][1], row[1][1])
                 for row in comp if (row[0] != row[1])]

for row in diff1990_2014:
    print(row)
print(f'\nThere are {len(diff1990_2014)} zone/subzone/variants '\
      'that change Koppen-Geiger classification when using the '\
      '1990-2014 data instead of the 1961-1990 data')
```

```
('BG  xh 1', 'Cfb', 'Cfa')
('BWBSdk', 'Dsc', 'Dfc')
('CMA unp', 'ET', 'Dfc')
('ESSFdcp', 'ET', 'Dfc')
('ESSFdh 1', 'Dfc', 'Dfb')
('ESSFdh 2', 'Dfc', 'Dfb')
('ESSFmh', 'Dfc', 'Dfb')
('ESSFmkp', 'ET', 'Dfc')
('ESSFvcp', 'ET', 'Dfc')
('ESSFwcp', 'ET', 'Dfc')
('ESSFxc 1', 'Dfc', 'Dsc')
('ESSFxcw', 'ET', 'Dfc')
('ESSFxv 1', 'ET', 'Dfc')
('ESSFxv 2', 'ET', 'Dfc')
('ICH dk', 'Dfc', 'Dfb')
('ICH mk 2', 'Dfc', 'Dfb')
('ICH mk 3', 'Dfc', 'Dfb')
('ICH mk 4', 'Dfc', 'Dfb')
('ICH mk 5', 'Dfc', 'Dfb')
('ICH mw 1', 'Dfc', 'Dfb')
('ICH vk 1', 'Dfc', 'Dfb')
('ICH wk 2', 'Dfc', 'Dfb')
('ICH xw', 'Dfb', 'Cfb')
('IDF dc', 'Dsc', 'Dfb')
('IDF dk 1', 'Dfc', 'Dfb')
('IDF dk 3', 'Dfc', 'Dfb')
('IDF dw', 'Dsc', 'Dfc')
('IDF ww', 'Dfb', 'Dsb')
('MH  mm 1', 'Dfc', 'Cfc')
('MH  unp', 'ET', 'Dfc')
('MH  wh 1', 'Dfc', 'Cfb')
('MS  dm 1', 'Dfc', 'Dfb')
('MS  dm 2', 'Dfc', 'Dfb')
('MS  dw', 'Dfc', 'Dfb')
('PP  xh 1', 'Dfb', 'Cfb')
('PP  xw', 'Dsb', 'Cfb')
('SBS dw 1', 'Dfc', 'Dfb')
('SBS mw', 'Dfc', 'Dfb')

There are 38 zone/subzone/variants that change Koppen-Geiger classification when using the 1990-2014 data inste
ad of the 1961-1990 data
```

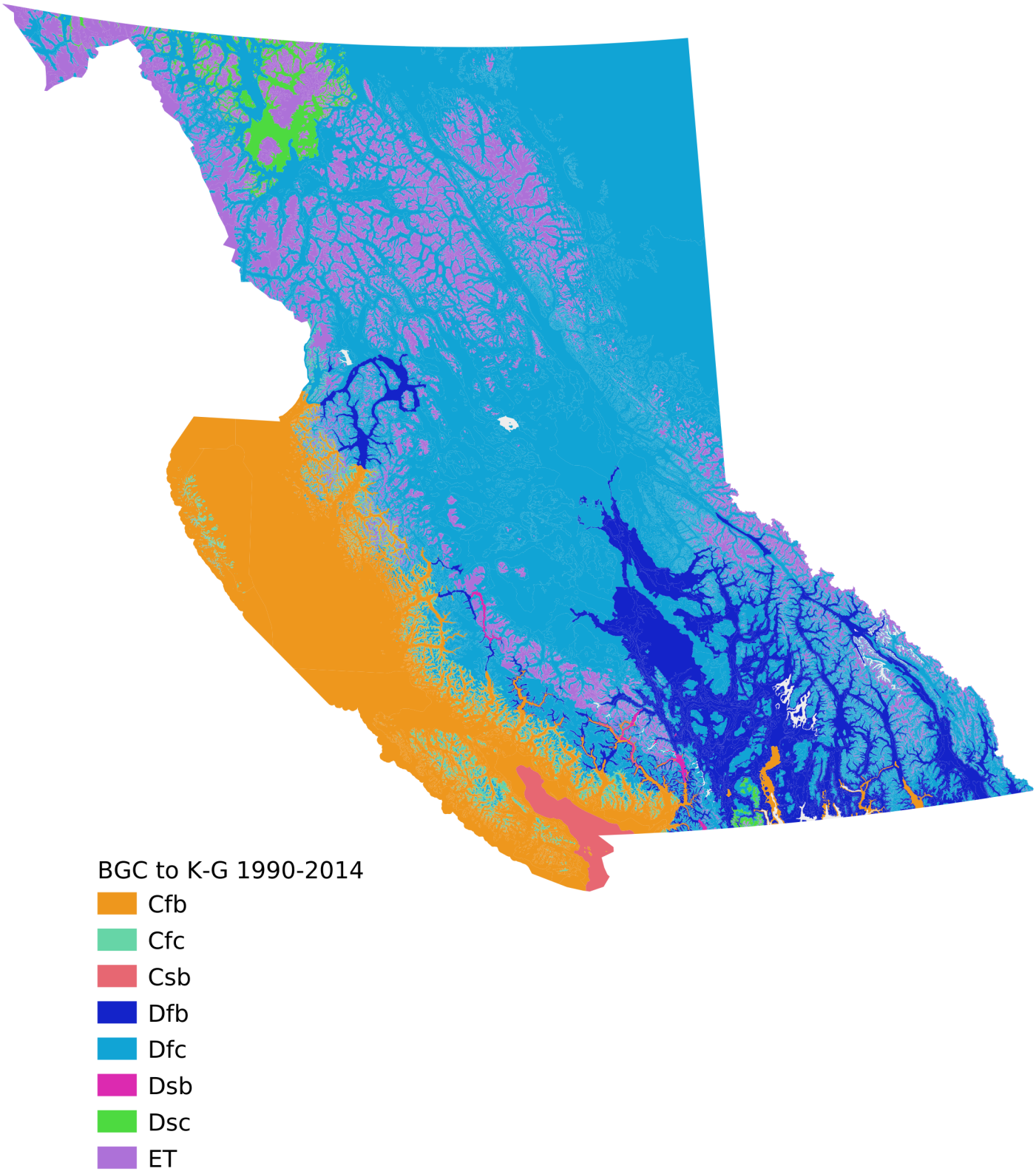
And map the 1990-2014 data, as well as the differences.

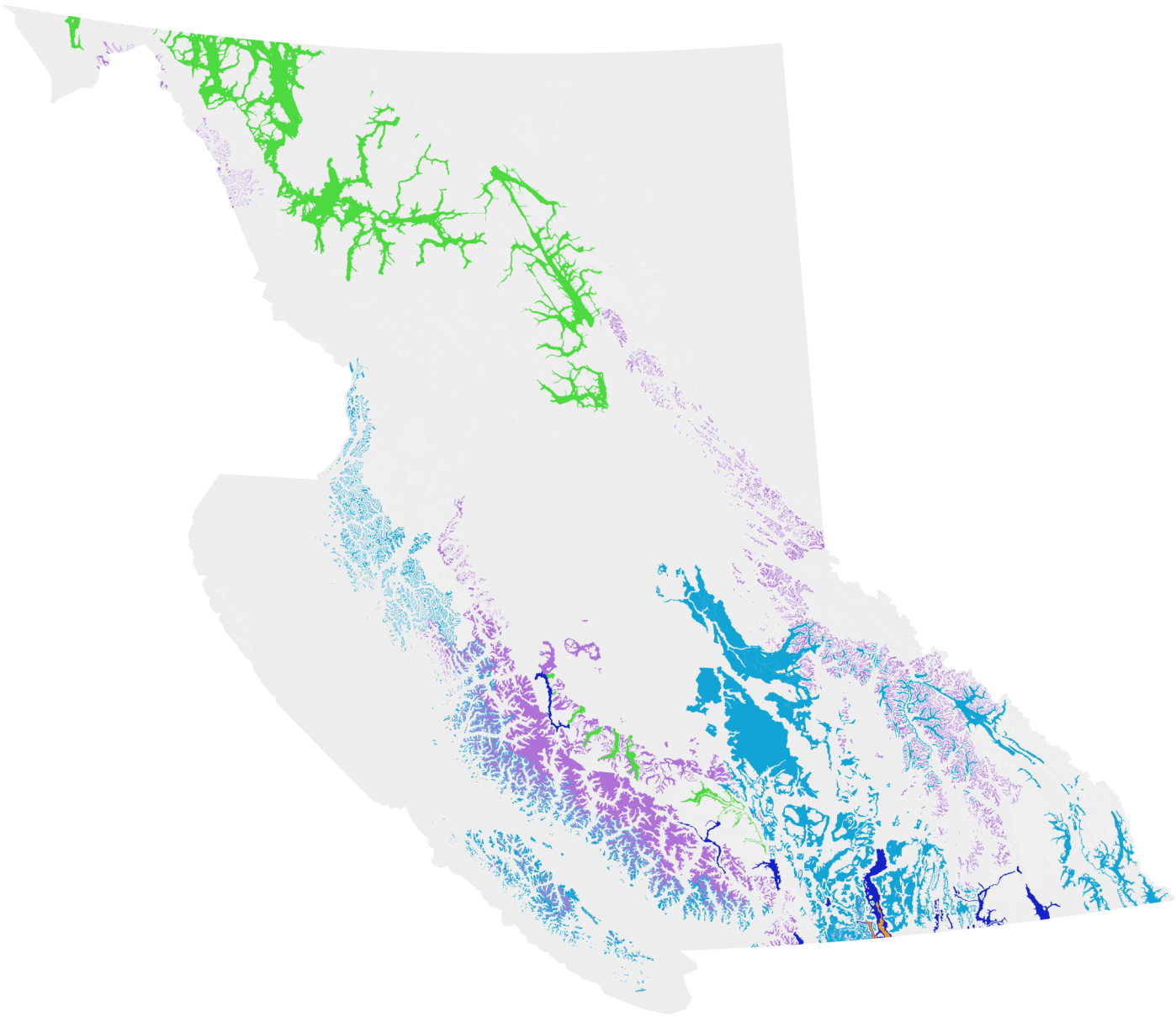
In [19]:

```
# Create a CSV of the 1990-2014 classification
with open('bec_2_k-g_1990_2014.csv','w') as f:
    w = csv.writer(f)

    # header row
    w.writerow(['BGC', 'KG'])
    # data rows
    for row in c2014:
        w.writerow(row)

# Create a CSV of the differences between 1961-1990 and 1990-2014
with open('bec_2_k-g_differences_1961-1990_1990-2014.csv','w') as f:
    w = csv.writer(f)

    # header row
    w.writerow(['BGC', 'KG1960-1992', 'KG1990-2014'])
    # data rows
    for row in diff1990_2014:
        w.writerow(row)
```

More maps

Now let's map those!


BGC to K-G 1990-2014
Cfb
Cfc
Csb
Dfb
Dfc
Dsb
Dsc
ET


Differences 1961-1991 to 1990-2014
Cfb
Cfc
Csb
Dfb
Dfc
Dsb
Dsc
ET

Difference in Koppen-Geiger classification in the South Okanagan between 1961-1990 and 1990-2014 climate datasets