Load Dataset

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

import warnings

# Suppress only a specific future warning
warnings.filterwarnings("ignore", message=".*use_inf_as_na option is depr
warnings.filterwarnings("ignore", message=".*Pass `(name,)` instead of `n
```

Dataset info:

Extracted Datasets for GEE:

MOD13A1(Frequency: 15days)

- NDVI
- EVI
- DetailedQA
- sur_refl_b01
- sur_refl_b02
- sur_refl_b03
- sur_refl_b07

ERA5_LAND(HOURLY)

- temperature_2m
- dewpoint_temperature_2m
- surface_pressure
- skin_temperature
- soil_temperature_level_1
- soil_temperature_level_2
- soil_temperature_level_3
- soil_temperature_level_4
- volumetric_soil_water_layer_1
- volumetric_soil_water_layer_2
- volumetric_soil_water_layer_3
- volumetric_soil_water_layer_4

CHIRPS (Weekly):

- precipitation

In [3]:

```
data_path = {
    'sentinel': "/kaggle/input/climate-crop/Sentinel_2_NDVI_Timeseries.cs
    "MOD13A1": '/kaggle/input/climate-crop/NDVI_Timeseries_3km_MyRegion_2
    "MOD11A1" : '/kaggle/input/climate-crop/MODIS11A1_MyRegion_26july.csv
    "ERA5_LAND": '/kaggle/input/climate-crop/ERA5_land_3km_MyRegion_26jul
    "CHIRPS":'/kaggle/input/climate-crop/CHIRPS_3km_MyRegion_26july.csv'
}

data_description = {
    "MOD13A1":[
        {
            "feature_name":"NDVI",
            "unit":"",
            "scale":0.0001,
            "offset": 0,
            "min":-2000,
            "max": 10000,
            "description" : "Normalized Difference Vegetation Index"
        },

        {
            "feature_name":"EVI",
            "unit":"",
            "scale":0.0001,
            "offset": 0,
            "min":-2000,
            "max": 10000,
            "description":"Enhanced Vegetation Index"
        },

        {
            "feature_name":"DetailedQA",
            "unit": "",
            "scale": 1,
            "offset" : 0,
            "description":"VI quality indicators"
        },

        {
            "feature_name":"sur_refl_b01",
            "unit": "",
            "scale": 0.0001,
            "offset" : 0,
            "min":0,
            "max": 10000,
            "wavelength":"645mm",
            "description":"Red surface reflectance"
        },
        {
            "feature_name":"sur_refl_b02",
            "unit": "",
            "scale": 0.0001,
            "offset" : 0,
            "min":0,
            "max": 10000,
            "wavelength":"645mm",
            "description": "NIR surface reflectance"
        },
        {
            "feature_name":"sur_refl_b03",
            "unit": "",
            "scale": 0.0001,
            "offset" : 0
```

```
            "offset" : 0,
            "min":0,
            "max": 10000,
            "wavelength":"645mm",
            "description":"Blue surface reflectance"
        },
        {
            "feature_name":"sur_refl_b07",
            "unit": "",
            "scale": 0.0001,
            "offset" : 0,
            "min":0,
            "max": 10000,
            "wavelength":"2130nm/2105 - 2155nm",
            "description":"MIR surface reflectance"
        },

        {
            "feature_name":"SummaryQA",
            "unit": "",
            "scale": 1,
            "offset" : 0,
            "description": "Quality reliability of VI pixel"
        }
        ],

    "MOD11A1":[

        {
            "feature_name":"LST_Day_1km",
            "unit": "K",
            "scale": 0.02,
            "offset" : 0,
            "min":7500,
            "max": 65535,
            "description": "Daytime Land Surface Temperature"
        },
        {
            "feature_name":"QC_Day",
            "unit": "",
            "scale": 1,
            "offset" : 0,
            "description": "Daytime LST Quality Indicators"
        },
        {
            "feature_name":"LST_Night_1km",
            "unit": "K",
            "scale": 0.02,
            "offset" : 0,
            "min":7500,
            "max": 65535,
            "description": "Nighttime Land Surface Temperature"
        }
    ],

    "ERA5_LAND":[
        {
            "feature_name":"temperature_2m",
            "unit": "K",
            "scale": 1,
            "offset" : 0,
            "description": "Temperature to which the air, at 2 meters abo
        },
```

```
{
    "feature_name":"dewpoint_temperature_2m",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature to which the air, at 2 meters abo
},

{
    "feature_name":"surface_pressure",
    "unit": "Pa",
    "scale": 1,
    "offset" : 0,
    "description": "Pressure (force per unit area) of the atmosph
},

{
    "feature_name":"skin_temperature",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature of the surface of the Earth."
},

{
    "feature_name":"soil_temperature_level_1",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature of the soil in layer 1 (0 - 7 cm)
},

{
    "feature_name":"soil_temperature_level_2",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature of the soil in layer 2 (7-28 cm)"
},

{
    "feature_name":"soil_temperature_level_3",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature of the soil in layer 2 (28-100 cm
},

{
    "feature_name":"soil_temperature_level_4",
    "unit": "K",
    "scale": 1,
    "offset" : 0,
    "description": "Temperature of the soil in layer 2 (100-289 c
},

{
    "feature_name":"volumetric_soil_water_layer_1",
    "unit": "Volume fraction",
    "scale": 1,
    "offset" : 0,
    "description": "Volume of water in soil layer 1 (0 - 7 cm)"
},
```

```
        {
            "feature_name":"volumetric_soil_water_layer_2",
            "unit": "Volume fraction",
            "scale": 1,
            "offset" : 0,
            "description": "Volume of water in soil layer 2 (7 - 28 cm)"
        },

        {
            "feature_name":"volumetric_soil_water_layer_3",
            "unit": "Volume fraction",
            "scale": 1,
            "offset" : 0,
            "description": "Volume of water in soil layer 3 (28 - 100 cm)
        },

        {
            "feature_name":"volumetric_soil_water_layer_4",
            "unit": "Volume fraction",
            "scale": 1,
            "offset" : 0,
            "description": "Volume of water in soil layer 4 (100 - 289 cm
        }
    ],
    "sentinel": [
            {'feature_name': 'QA20',
              'unit': '',
              'scale': 1,
              'offset': 0,
              'description': ''},

             {'feature_name': 'B2',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'B10',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'B11',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'B8',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'B9',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'B7',
              'unit': '',
              'scale': 0.0001,
              'offset': 0,
              'description': ''},
             {'feature_name': 'NDVI',
```

```
             'unit': '',
             'scale': 1,
             'offset': 0,
             'description': ''},

            {'feature_name': 'B3',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},

            {'feature_name': 'B5',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
            {'feature_name': 'B12',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
            {'feature_name': 'B4',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
            {'feature_name': 'B8A',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
            {'feature_name': 'B1',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
            {'feature_name': 'B6',
             'unit': '',
             'scale': 0.0001,
             'offset': 0,
             'description': ''},
           ],

    "CHIRPS":[

        {
            "feature_name":"precipitation",
            "unit": "mm/pentad",
            "scale": 1,
            "offset" : 0,
            "min": 0,
            "max": 1072,
            "description": "Precipitation"
        }

    ]
}
```

Read Data

In [4]:
```
data_collection = {}

for name,path in data_path.items():

    df = pd.read_csv(path)

    for feature_disc in data_description[name]:
        feature_name  = feature_disc['feature_name']

        stats = ["_mean","_max","_min","_stdDev"]
        feature_name_stat = [feature_name + s for s in stats ]

        if('scale' in feature_disc):
                scale = feature_disc['scale']
        else:
            scale = 1


        if('offset' in feature_disc):
            offset = feature_disc['offset']
        else:
            offset = 0

        for fn in feature_name_stat:

            df[fn] = df[fn]*scale + offset

        if('.geo' in df.columns):
            df.drop(columns = '.geo',inplace = True)


        data_collection[name] = df.copy()
```

columns arrangements

In [5]:
```
####
columns_modis_13A1 = ['date', 'region', 'state','buffer_km','DetailedQA_m
       'DetailedQA_stdDev', 'EVI_max', 'EVI_mean', 'EVI_min', 'EVI_stdDev
       'NDVI_max', 'NDVI_mean', 'NDVI_min', 'NDVI_stdDev', 'SummaryQA_max
       'SummaryQA_mean', 'SummaryQA_min', 'SummaryQA_stdDev', 'sur_refl_b
       'sur_refl_b01_min', 'sur_refl_b01_stdDev', 'sur_refl_b02_max',
       'sur_refl_b02_mean', 'sur_refl_b02_min', 'sur_refl_b02_stdDev',
       'sur_refl_b03_max', 'sur_refl_b03_mean', 'sur_refl_b03_min',
       'sur_refl_b03_stdDev', 'sur_refl_b07_max', 'sur_refl_b07_mean',
       'sur_refl_b07_min', 'sur_refl_b07_stdDev']

data_collection['MOD13A1'] = data_collection['MOD13A1'][columns_modis_13A
data_collection['MOD13A1']['date'] = pd.to_datetime(data_collection['MOD1
data_collection['MOD13A1'] = data_collection['MOD13A1'].sort_values(['dat

#####


columns_modis_11A1 = [ 'date', 'region', 'state' , 'buffer_km', 'LST_Day_
       'LST_Day_1km_min', 'LST_Day_1km_stdDev', 'LST_Night_1km_max',
       'LST_Night_1km_mean', 'LST_Night_1km_min', 'LST_Night_1km_stdDev',
       'QC_Day_max', 'QC_Day_mean', 'QC_Day_min', 'QC_Day_stdDev']

data_collection['MOD11A1'] = data_collection['MOD11A1'][columns_modis_11A

data_collection['MOD11A1']['date'] = pd.to_datetime(data_collection['MOD1
data_collection['MOD11A1'] = data_collection['MOD11A1'].sort_values(['dat


data_collection['CHIRPS'].columns


####
CHIRPS_columns =[ 'date','state','region','buffer_km', 'precipitation_max
       'precipitation_mean', 'precipitation_min', 'precipitation_stdDev']

data_collection['CHIRPS'] = data_collection['CHIRPS'][CHIRPS_columns]
data_collection['CHIRPS']['date'] = pd.to_datetime(data_collection['CHIRP
data_collection['CHIRPS'] = data_collection['CHIRPS'].sort_values(['date'


####
ERA5_LAND_columns = ['date','state','buffer_km','region','dewpoint_temper
       'dewpoint_temperature_2m_mean', 'dewpoint_temperature_2m_min',
       'dewpoint_temperature_2m_stdDev', 'skin_temperature_max',
       'skin_temperature_mean', 'skin_temperature_min',
       'skin_temperature_stdDev', 'soil_temperature_level_1_max',
       'soil_temperature_level_1_mean', 'soil_temperature_level_1_min',
       'soil_temperature_level_1_stdDev', 'soil_temperature_level_2_max',
       'soil_temperature_level_2_mean', 'soil_temperature_level_2_min',
       'soil_temperature_level_2_stdDev', 'soil_temperature_level_3_max',
       'soil_temperature_level_3_mean', 'soil_temperature_level_3_min',
       'soil_temperature_level_3_stdDev', 'soil_temperature_level_4_max',
       'soil_temperature_level_4_mean', 'soil_temperature_level_4_min',
       'soil_temperature_level_4_stdDev', 'surface_pressure_max',
       'surface_pressure_mean', 'surface_pressure_min',
       'surface_pressure_stdDev', 'temperature_2m_max', 'temperature_2m_m
       'temperature_2m_min', 'temperature_2m_stdDev',
       'volumetric_soil_water_layer_1_max',
       'volumetric_soil_water_layer_1_mean',
       'volumetric_soil_water_layer_1_min',
       'volumetric_soil_water_layer_1_stdDev',
       'volumetric_soil_water_layer_2_max',
```

```
        'volumetric_soil_water_layer_2_max',
        'volumetric_soil_water_layer_2_mean',
        'volumetric_soil_water_layer_2_min',
        'volumetric_soil_water_layer_2_stdDev',
        'volumetric_soil_water_layer_3_max',
        'volumetric_soil_water_layer_3_mean',
        'volumetric_soil_water_layer_3_min',
        'volumetric_soil_water_layer_3_stdDev',
        'volumetric_soil_water_layer_4_max',
        'volumetric_soil_water_layer_4_mean',
        'volumetric_soil_water_layer_4_min',
        'volumetric_soil_water_layer_4_stdDev']



data_collection['ERA5_LAND'] = data_collection['ERA5_LAND'][ERA5_LAND_col

data_collection['ERA5_LAND']['date'] = pd.to_datetime(data_collection['ER
data_collection['ERA5_LAND'] = data_collection['ERA5_LAND'].sort_values([
```

In [6]:

```
# data_collection['sentinel'].columns , ['NDVI_max', 'NDVI_mean', 'NDVI_m
```

In [7]:

```
senitenl_columns =[ 'date','state','region','buffer_km'] +  ['NDVI_max',

data_collection['sentinel'] = data_collection['sentinel'][senitenl_column
data_collection['sentinel']['date'] = pd.to_datetime(data_collection['sen
data_collection['sentinel'] = data_collection['sentinel'].sort_values(['d
```

Mark months to crop

In [8]:

```
# !pip install --upgrade seaborn -q
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [9]:

```
df = data_collection['MOD13A1'].copy()
df['month'] = df['date'].map(lambda x: x.month)
df['year'] = df['date'].map(lambda x: x.year)
df = df.sort_values("date")
data_collection['MOD13A1'] = df

df = data_collection['sentinel'].copy()
df['month'] = df['date'].map(lambda x: x.month)
df['year'] = df['date'].map(lambda x: x.year)
df = df.sort_values("date")
data_collection['sentinel'] = df
data_collection['sentinel'] = data_collection['sentinel'].dropna(axis=0)
```

In [10]:

```
def ema(data, alpha):
    ema_vals = [data[0]]  # start with the first data point
    for val in data[1:]:
        ema_vals.append(alpha * val + (1 - alpha) * ema_vals[-1])
    return ema_vals
```

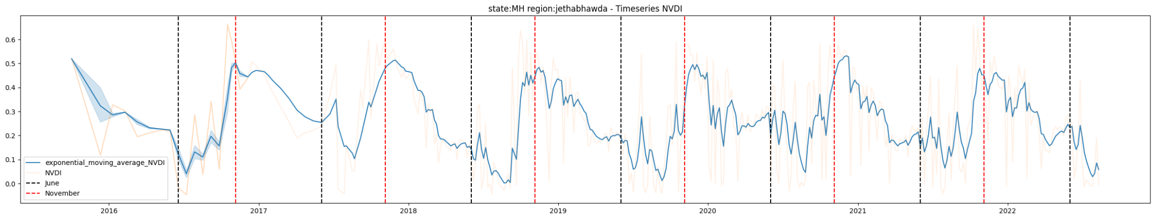
In [11]:

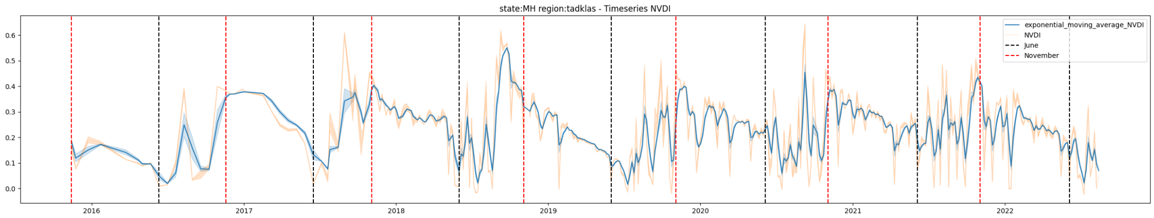
```
# df_2 = df_1.groupby(['state','region','year','crop' ])[['NDVI_mean','ND
```

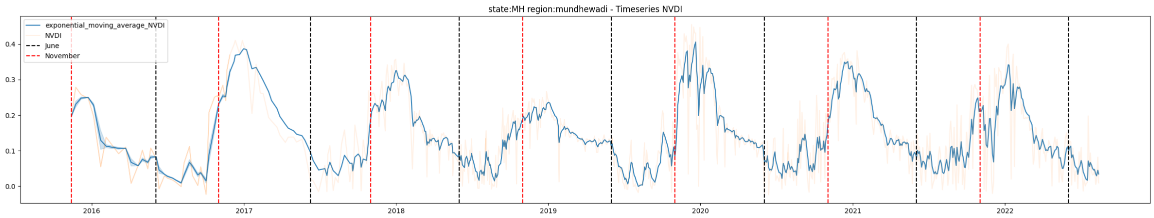
In [12]:
```python
##classify crop based on the months
def func_crop_mp(x):
    if(x>=7 and x<11):
        return 'kharif'
    elif(x>=11 or x<=4):
        return 'rabi'
    else:
        return 'nocrop'

def func_crop_MH(x):
    if(x>=6 and x<10):
        return 'kharif'
    elif(x>=10 or x<6):
        return 'rabi'
    else:
        return 'nocrop'

def fun_mark_crop(data):

    state = data.state.unique()
    dfs = []

    for s in state:

        if(s =='MP'):
            df =  data[data.state == s].copy()
            df['crop'] = df['month'].map(func_crop_mp)
            dfs.append(df)

        elif(s == 'MH'):
            df =  data[data.state == s].copy()
            df['crop'] = df['month'].map(func_crop_MH)
            dfs.append(df)

    dfs = pd.concat(dfs,axis =0)
    return dfs


data_collection['sentinel'] = fun_mark_crop(data_collection['sentinel'])
data_collection['MOD13A1'] = fun_mark_crop(data_collection['MOD13A1'])
```

In [12]:
```
df_1 = data_collection['sentinel'].copy()
df_2 = data_collection['MOD13A1'].groupby(['state','region','year','crop'


crops = ['kharif','rabi']
state = ['MH','MP']#,'MH']
# state = ['MP']#,'MH']


for s in state:

    df_3 = df_1[(df_1.state == s) ].copy().iloc[:2000]
    # NDVI_mean plot

    for region in df_3.region.unique():

        data = df_3[df_3.region == region]['NDVI_mean'].values
        date = df_3[df_3.region == region]['date'].values

        data = np.array(list(data))
        if(s =='MH'):
            alpha = 0.3
        else:
            alpha = 0.3

        ema_vals = np.array(ema(data, alpha=alpha))


        df_3_ = df_3[df_3.region == region]
        df_3_ = df_3_.loc[df_3_[['month','year']].drop_duplicates(keep =

        plt.figure(figsize = (30,5))
        sns.lineplot(x =date , y = ema_vals,alpha=0.9,label = 'exponentia
        sns.lineplot(x =date , y = data,alpha=0.1,label = 'NVDI')

        def add_vertical_line(dates,color,label):
            added_label = False
            for d in dates:
                if not added_label:
                    plt.axvline(x=d, color=color, linestyle='--', label=l
                    added_label = True
                else:
                    plt.axvline(x=d, color=color, linestyle='--')

        if(s == 'MP'):
            months = [7,11,4]
            labels = ['July','November','April']
            colors = ['black','red','blue']
        else:
            months = [6,11]
            labels = ['June','November']
            colors = ['black','red']




        for m ,c ,l in zip(months,colors,labels):
            date_vertical_line = df_3_[df_3_['month'] ==m]['date'].values
            add_vertical_line(date_vertical_line,color = c ,label = l )

        plt.legend()
        plt.title(f"state:{s} region:{region} - Timeseries NVDI")
        plt.show()
```

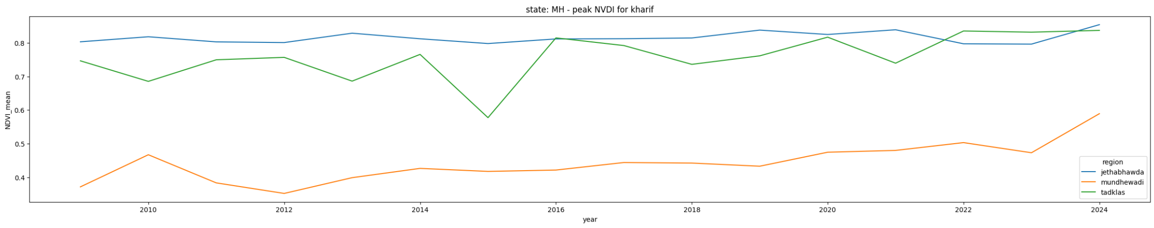
```
    plt.show()

for crop in crops:
    print(f"state:{s} crop:{crop}")
    df_4 = df_2[(df_2.state == s) & (df_2.crop ==crop ) ].copy()


    ##peak NVDI year on year
    plt.figure(figsize = (30,5))
    ax = sns.lineplot(data=df_4, x='year', y='NDVI_mean',hue = 'regio
    ax.set_title(f'state: {s} - peak NVDI for {crop}')

    plt.show()
```



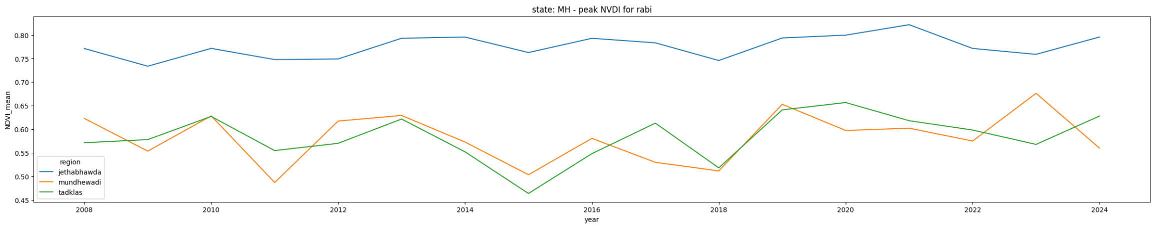


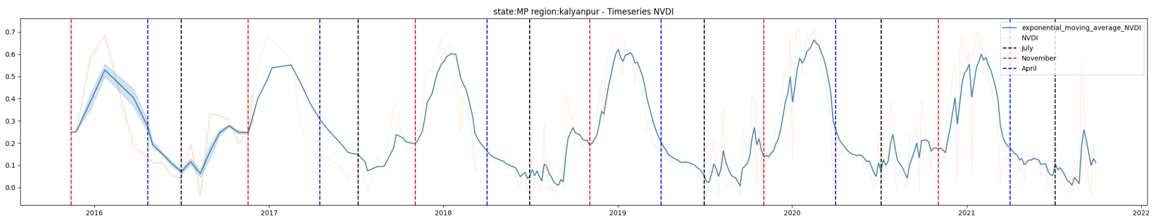


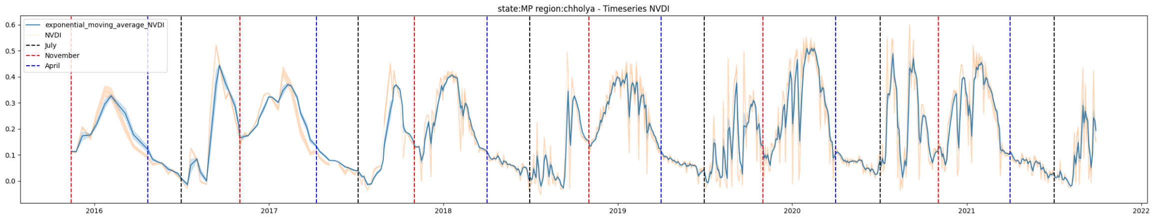

```
state:MH crop:kharif
```

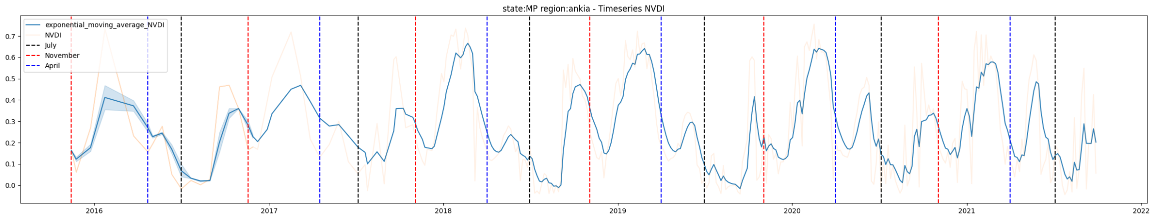



```
state:MH crop:rabi
```

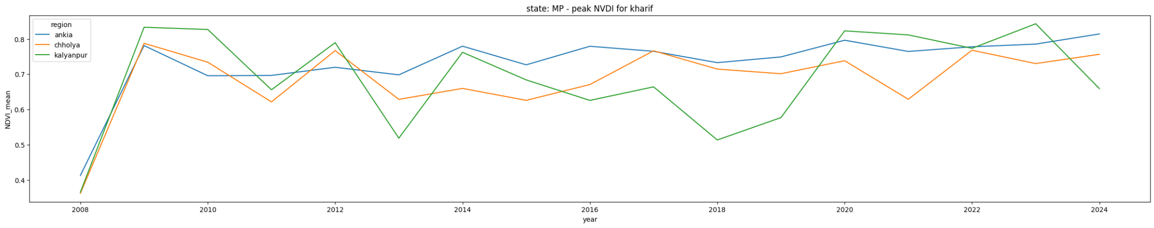




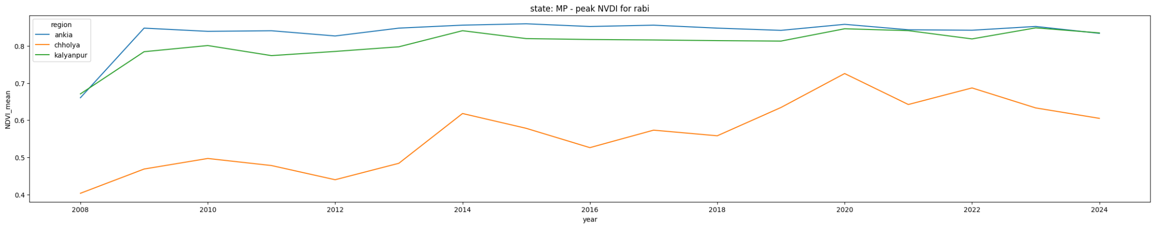





```
state:MP crop:kharif
```




```
state:MP crop:rabi
```



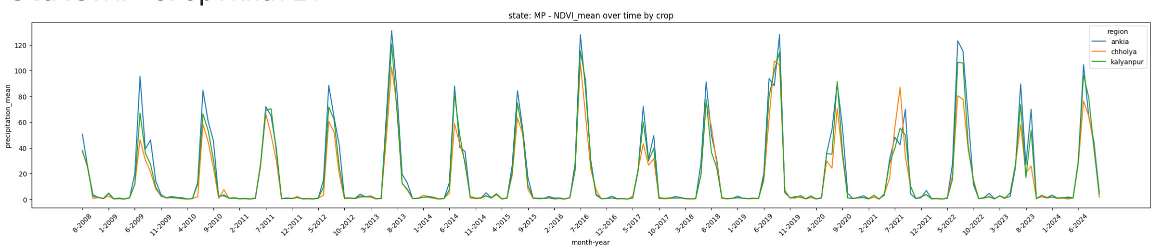
- MP region - has clear distinct on kharif and rabi crop
  - Kharif - July - November
  - Rabi - November - April
- MH region - has continous peak
  - Kharif - July - November
  - rabi November/Decemeber - May/June

Precepitation analysis

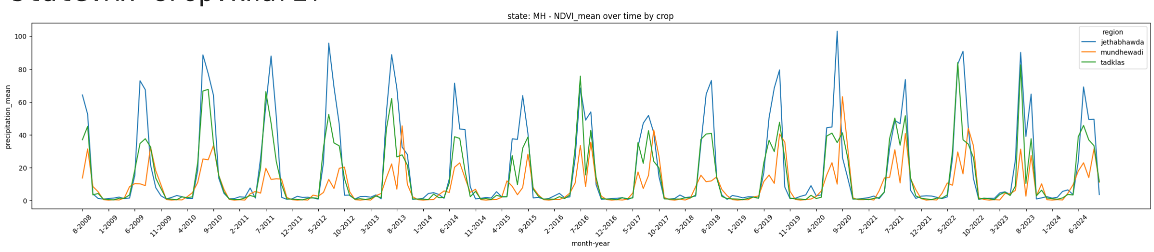
In [13]:
```
data_chirps = data_collection['CHIRPS'].copy()

data_chirps['month'] = data_chirps['date'].map(lambda x: x.month)
data_chirps['year'] = data_chirps['date'].map(lambda x: x.year)

# data_chirps['crop'] = data_chirps['month'].map(func_crop)
data_chirps = fun_mark_crop(data_chirps)

data_chirps = data_chirps.sort_values("date")
data_collection['CHIRPS'] = data_chirps
```

In [16]:
```
data_chirps_grp =  data_chirps.groupby(['year','month','state','region','
# data_chirps_grp['month_year']

data_chirps_grp['month-year'] = data_chirps_grp[['month','year']].apply(f

crops = ['kharif']
state = ['MP','MH']

for s in state:
    for crop in crops:
        print(f"state:{s} crop:{crop}")
        df = data_chirps_grp.copy()
        df =  df[(df.state == s)].copy()
        # df_1 =  df[(df.crop ==region)].copy()

        # NDVI_mean plot
        plt.figure(figsize = (30,5))
        ax = sns.lineplot(data = df, x='month-year', y='precipitation_mea
        ax.set_title(f'state: {s} - NDVI_mean over time by crop')

        xticks = df['month-year'].unique()[::5]  # every 4th tick
        ax.set_xticks([])
        ax.set_xticks(xticks)
        ax.tick_params(axis='x', rotation=45)

        plt.show()
```

```
state:MP crop:kharif
```




```
state:MH crop:kharif
```



- MP: During 2013,2016,2022 - There was was heavy rainfall
- MH:
  - Mundhewadi had very less precipitation: That is clearly seen this region has no Kharif Peaks.

In [14]:
```
### Merge NDVI and precipitation data

def func(x,df_2):

    offset = pd.DateOffset(months=0, days=15)

    x1 = x.iloc[0]
    x2 = x.iloc[1]

    if(pd.isna(x1)):
        return np.NaN
    elif(pd.isna(x2)):
        x2 = x1 - offset
    else:
        pass

    df_2 = df_2[(df_2['date'] <=x1) & (df_2['date'] > x2) ]

    mean_val = df_2[['precipitation_max','precipitation_mean', 'precipita

    mean_val['date'] = x1

    return mean_val
data_ndvi = data_collection['MOD13A1'].copy()

data_ndvi_pre = []

for (s,r),grp in data_ndvi.groupby(['state','region']):
    grp['prev_date'] = grp['date'].shift(1)

    df_2 = data_chirps[(data_chirps['state'] == s) & (data_chirps['region

    mean_val =  grp[['date','prev_date','state','region']].apply(lambda x

    mean_val['state'] = s
    mean_val['region'] = r

    data_ndvi_pre.append(mean_val)

data_ndvi_pre = pd.concat(data_ndvi_pre,axis = 0)
data_ndvi_precipitation =  data_ndvi.merge(data_ndvi_pre , on =['date','r
```

Analysis on NVDI peak over preciptation

In [15]:
```
### year on year
columns_to_corr = [ 'NDVI_max', 'NDVI_mean','NDVI_min', 'precipitation_ma

data_ndvi_year_crop = data_ndvi_precipitation.groupby(['state','region','
    NDVI_peak =pd.NamedAgg(column="NDVI_mean", aggfunc="max"),
    precipitation_mean =pd.NamedAgg(column="precipitation_mean", aggfunc=
    precipitation_max =pd.NamedAgg(column="precipitation_mean", aggfunc="
    precipitation_std =pd.NamedAgg(column="precipitation_mean", aggfunc="

data_ndvi_year_crop = data_ndvi_year_crop.reset_index()
```

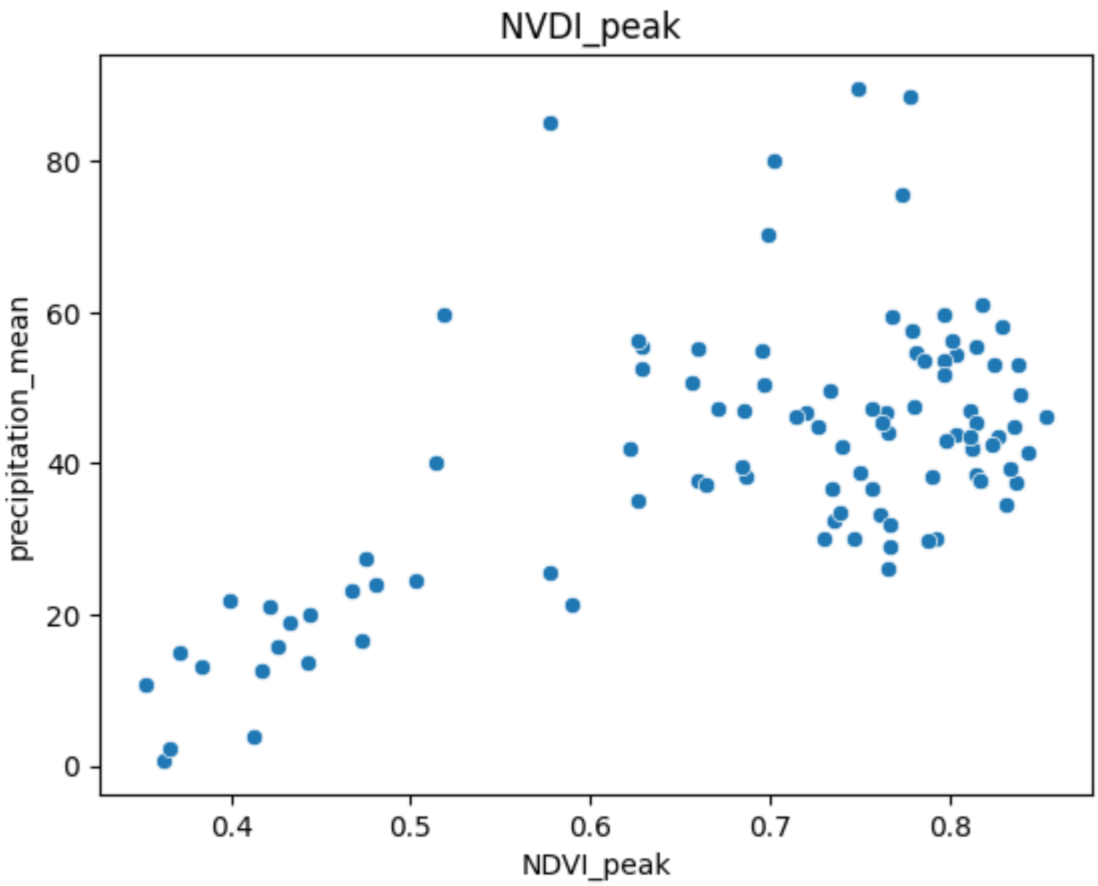
In [16]:
```
data_ndvi_year_crop[data_ndvi_year_crop.crop == 'kharif'].groupby('state'
```

Out[16]:

		NDVI_peak	precipitation_mean	precipitation_max	precipitation_std
state					
MH	**NDVI_peak**	1.000000	0.861122	0.739630	0.655773
	precipitation_mean	0.861122	1.000000	0.853197	0.790803
	precipitation_max	0.739630	0.853197	1.000000	0.957131
	precipitation_std	0.655773	0.790803	0.957131	1.000000
MP	**NDVI_peak**	1.000000	0.391582	0.385511	0.357111
	precipitation_mean	0.391582	1.000000	0.864270	0.814800
	precipitation_max	0.385511	0.864270	1.000000	0.973891
	precipitation_std	0.357111	0.814800	0.973891	1.000000

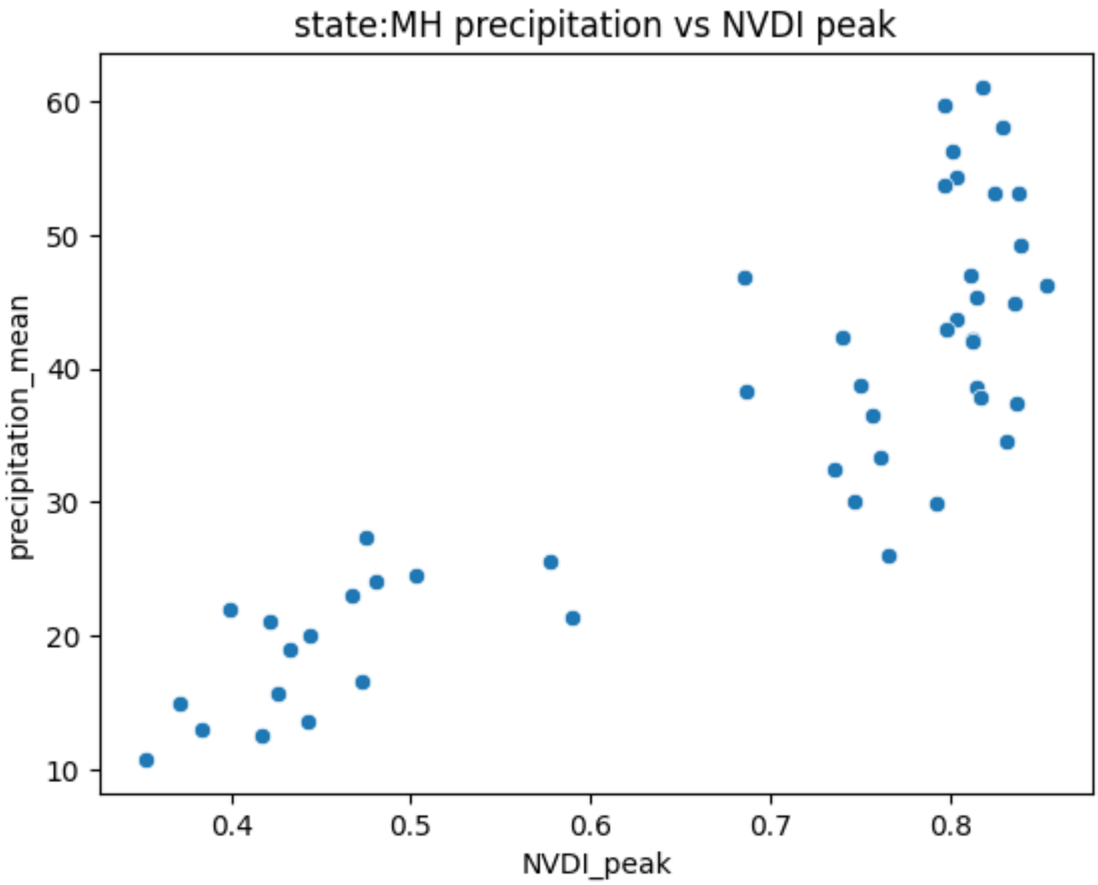
In [17]:

```
sns.scatterplot(x = 'NDVI_peak',y = 'precipitation_mean',data = data_ndvi
plt.title(f"NVDI_peak ")
plt.show()
```

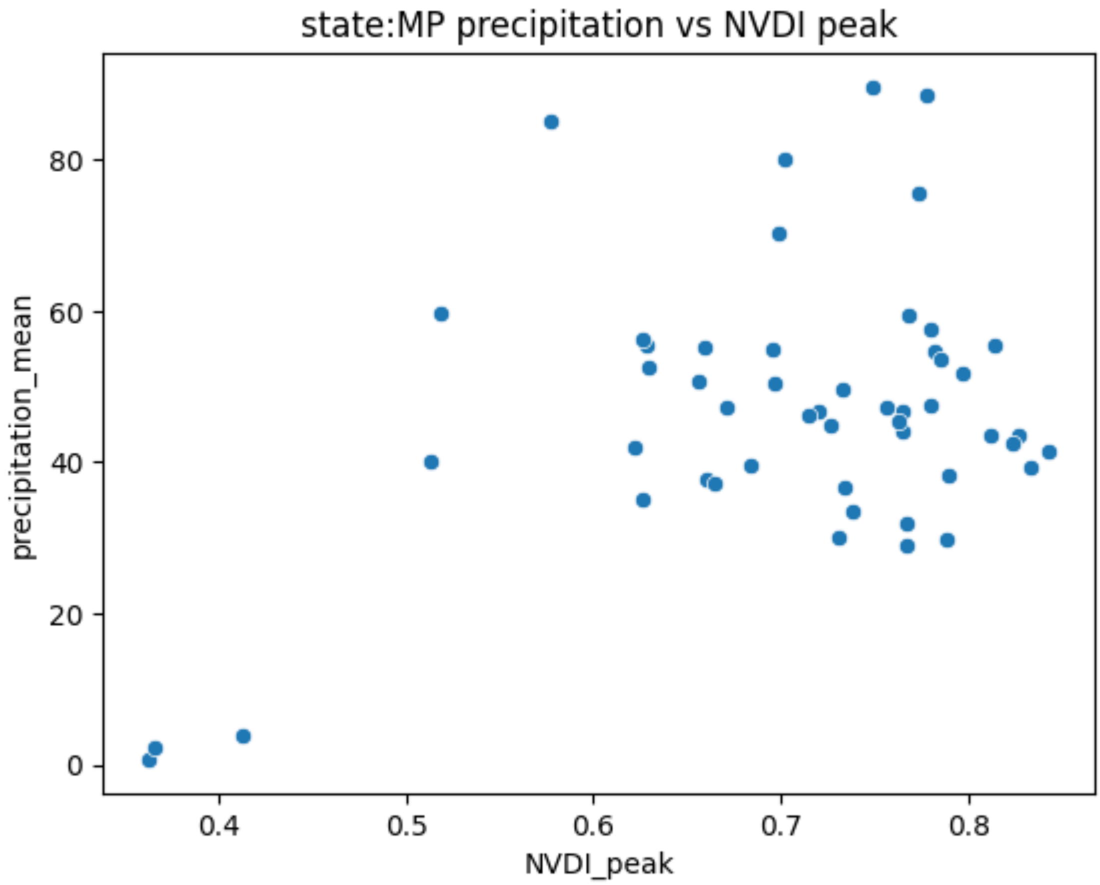


- NVDI peak is correlating with precipitation

In [60]:
```
#'EVI_max','EVI_mean', 'EVI_min', 'EVI_stdDev',

columns_to_corr = [ 'NVDI_peak', 'precipitation_mean', 'precipitation_std


# regions = data_nvdi_precipitation[data_nvdi_precipitation.state == 'MP'


for state  in data_nvdi_year_crop.state.unique():

    df = data_nvdi_year_crop[data_nvdi_year_crop.state == state ].copy()

    sns.scatterplot(x = 'NVDI_peak',y = 'precipitation_mean',data = df[ (
    plt.title(f"state:{state} precipitation vs NVDI peak")
    plt.show()


    # fig,axis = plt.subplots(nrows = 1,ncols = 3,figsize = (30,5))


    for i,region in enumerate(df.region.unique()):

        print(f"region:{region}")

        grp = df[ (df.crop == 'kharif') &
                  ( df.region  == region ) ]

        corr = grp[columns_to_corr].corr()

        print(f"",corr['NVDI_peak'].to_dict())

        # sns.scatterplot(x = 'NVDI_peak',y = 'precipitation_mean',data =
        # plt.title(f'state:{s} region:{region}- plot ')
        # plt.show()
```




```
region:jethabhawda
 {'NVDI_peak': 1.0, 'precipitation_mean': -0.03296094341898041, 'precipit
ation_std': -0.10295944202284003}
region:mundhewadi
 {'NVDI_peak': 1.0, 'precipitation_mean': 0.6093342342239988, 'precipitat
ion_std': 0.2895558937319416}
region:tadklas
 {'NVDI_peak': 1.0, 'precipitation_mean': 0.25343896516580444, 'precipita
tion_std': 0.3025331967625471}
```




```
region:ankia
 {'NVDI_peak': 1.0, 'precipitation_mean': 0.6333165313716916, 'precipitat
ion_std': 0.7003937873767907}
region:chholya
 {'NVDI_peak': 1.0, 'precipitation_mean': 0.39135190160073674, 'precipita
tion_std': 0.2578683551461847}
region:kalyanpur
 {'NVDI_peak': 1.0, 'precipitation_mean': 0.16938443195431488, 'precipita
tion_std': 0.14056152811403586}
```

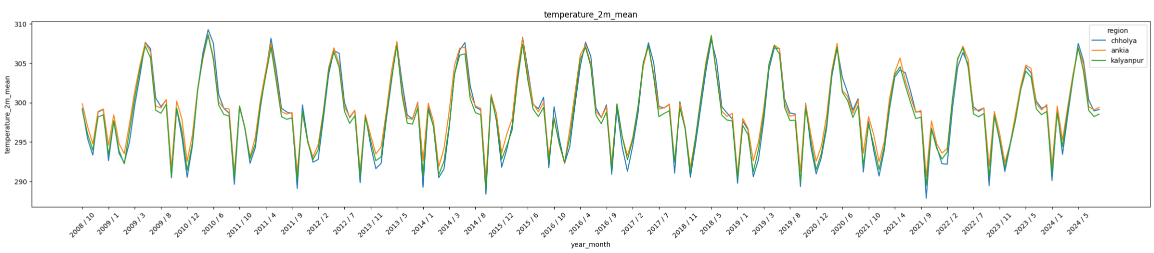
- MH show signficant correlation with precipitation, unitl 0.6 and 30mm precipitation and after than it's governerd by other factors.

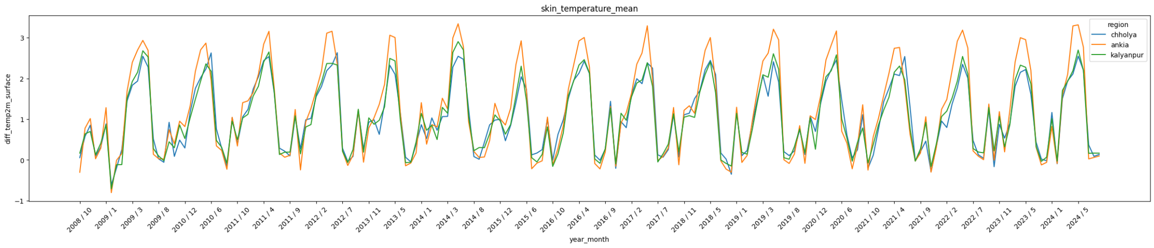
Tempreture and Moisutre Analysis

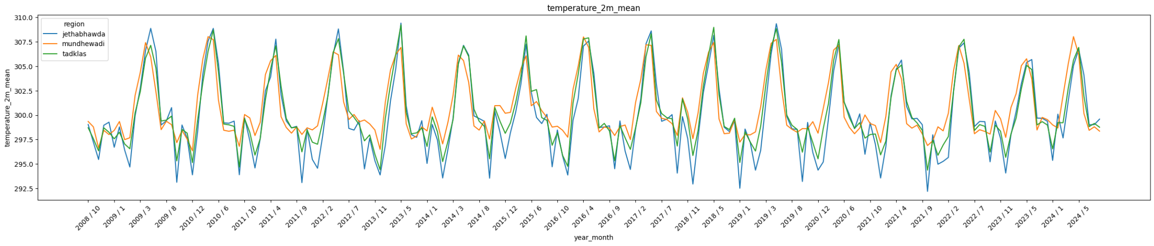
In [17]:
```
data_era = data_collection['ERA5_LAND'].copy()
data_era['month'] = data_era['date'].map(lambda x:x.month)
data_era['year'] = data_era['date'].map(lambda x:x.year)


data_era["dewpoint_depression"] = data_era["temperature_2m_mean"]  - data
data_era["surface_air_Temp_Diff"] = data_era["skin_temperature_mean"] - d
data_era["ratio_surface_air_temp"]  =   (data_era["temperature_2m_mean"]


columns_plot = ['temperature_2m_mean','dewpoint_temperature_2m_mean','ski
                'dewpoint_depression','surface_air_Temp_Diff','ratio_surfa
                ]

data_era_month =  data_era.groupby(['region','month','year','state'])[col
data_era_month = data_era_month.reset_index().sort_values(['region','mont

data_era_month['year_month'] = data_era_month[ ['year','month']].apply(la
data_era_month = data_era_month.sort_values('year_month')

# data_era_month['diff_temp2m_surface'] = (-data_era_month['temperature_2
```

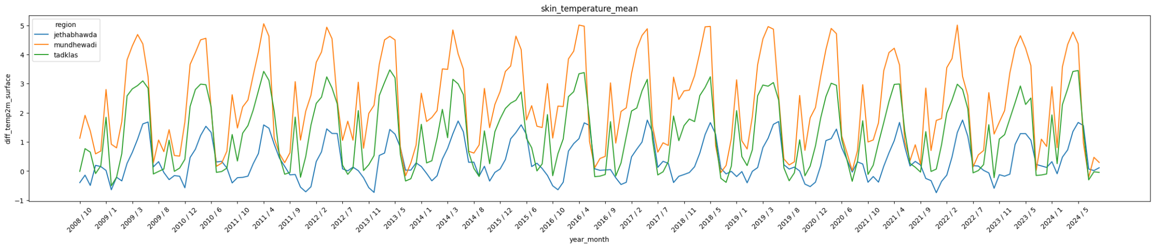
In [18]:
```
# data_era_month
```

In [28]:
```
crops = ['kharif','rabi']
state = ['MP','MH']

for s in state:
    # for crop in crops:
    # print(f"state:{s} crop:{crop}")

    # tempreture plot
    plt.figure(figsize = (30,5))
    ax = sns.lineplot(data=data_era_month[data_era_month.state == s], x='
    ax.set_title(f'state: {s} - temperature_plot')

    xticks = list(data_era_month[data_era_month.state == s]['year_month']

    plt.xticks(xticks,rotation=45)
    plt.title('temperature_2m_mean')
    plt.show()

    # tempreture plot
    plt.figure(figsize = (30,5))
    ax = sns.lineplot(data=data_era_month[data_era_month.state == s], x='
    ax.set_title(f'state: {s} - temperature_plot')

    xticks = list(data_era_month[data_era_month.state == s]['year_month']

    plt.xticks(xticks,rotation=45)
    plt.title('skin_temperature_mean')
    plt.show()
```




skin_temperature_mean
region
chholya
ankia
kalyanpur
diff_temp2m_surface
year_month


temperature_2m_mean
region
jethabhawda
mundhewadi
tadklas
temperature_2m_mean
year_month

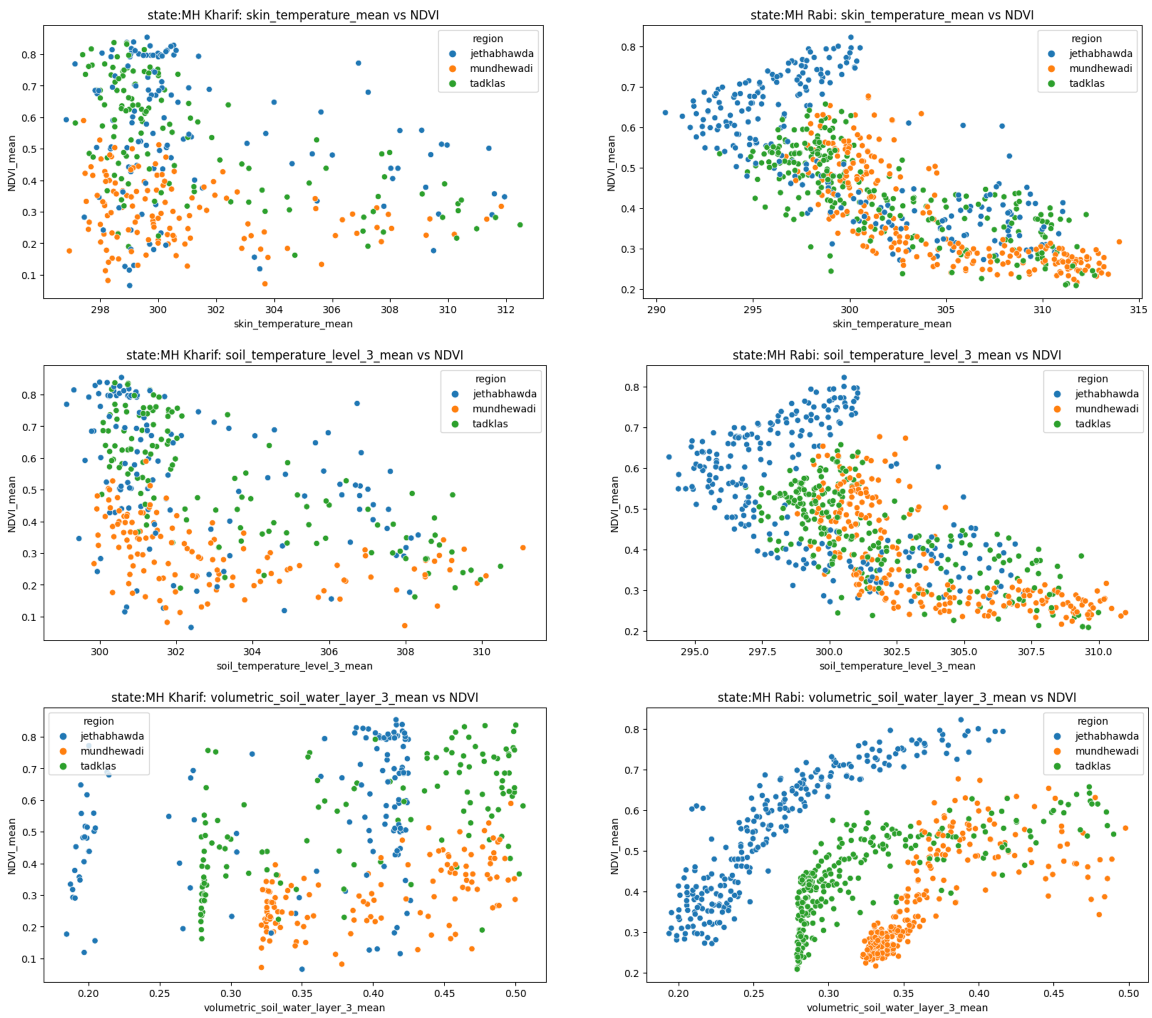

skin_temperature_mean
region
jethabhawda
mundhewadi
tadklas
diff_temp2m_surface
year_month

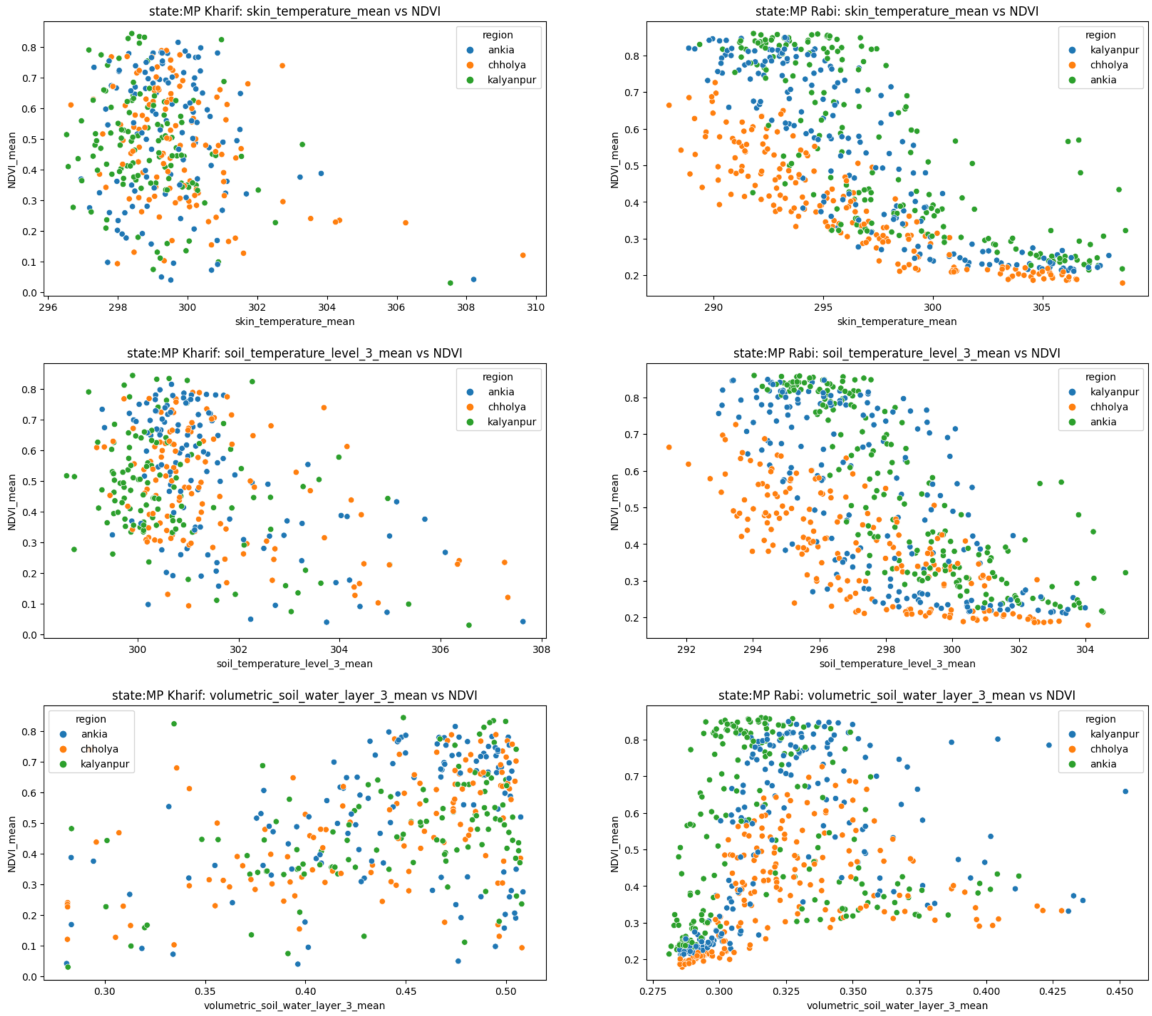
In [19]:
```
### merge all data sets

def func(x,df_2):

    offset = pd.DateOffset(months=0, days=15)

    x1 = x.iloc[0]
    x2 = x.iloc[1]

    if(pd.isna(x1)):
        return np.NaN
    elif(pd.isna(x2)):
        x2 = x1 - offset
    else:
        pass

    df_2 = df_2[(df_2['date'] <=x1) & (df_2['date'] > x2) ]

    columns = ['temperature_2m_mean','dewpoint_temperature_2m_mean','skin
  'soil_temperature_level_4_mean', 'surface_pressure_mean','volumetric_so
 'dewpoint_depression','surface_air_Temp_Diff','ratio_surface_air_temp']

    mean_val = df_2[columns].mean()

    mean_val['date'] = x1

    return mean_val


data_merged = []

for (s,r),grp in data_ndvi_precipitation.groupby(['state','region']):
    grp['prev_date'] = grp['date'].shift(1)

    df_2 = data_era[(data_era['state'] == s) & (data_era['region'] == r)]

    mean_val =  grp[['date','prev_date','state','region']].apply(lambda x

    mean_val['state'] = s
    mean_val['region'] = r

    data_merged.append(mean_val)

data_merged = pd.concat(data_merged,axis = 0)
# data_nvdi_precipitation =  data_nvdi.merge(data_ndvi_pre , on =['date',
data_merged =  data_ndvi_precipitation.merge(data_merged , on =['date','r
```

In [ ]:

Plot on Temp, Volumetric soil

In [21]:
```
columns_to_corr = [ 'NDVI_max', 'NDVI_mean','NDVI_min'] + ['temperature_2
  'soil_temperature_level_4_mean', 'surface_pressure_mean','volumetric_so


columns_plot = ['skin_temperature_mean','soil_temperature_level_3_mean','


for state in data_merged.state.unique():

    grp = data_merged[(data_merged.state == state ) ]
    # corr = grp[columns_to_corr].corr()

    # print(corr['NDVI_mean'].to_dict())

    for col in columns_plot:

        fig,axes = plt.subplots(nrows = 1,ncols = 2,figsize = (20,5))

        sns.scatterplot(data =  grp[ (grp.crop == 'kharif')], x =  col ,y
        sns.scatterplot(data =  grp[ (grp.crop == 'rabi')], x = col ,y =

        axes[0].set_title(f'state:{state} Kharif: {col} vs NDVI')
        axes[1].set_title(f'state:{state} Rabi: {col} vs NDVI')

        plt.show()
    print('\n\n\n')
```





In [22]:
```
columns = ['NDVI_mean','EVI_mean'] + ['precipitation_mean','temperature_2
  'soil_temperature_level_4_mean', 'surface_pressure_mean','volumetric_so
  'dewpoint_depression','surface_air_Temp_Diff','ratio_surface_air_temp']

corr = data_merged[data_merged.crop !="nocrop"].groupby(['state','region'
corr = corr.loc[[i for i in corr.index if (i[-1] not in ['EVI_mean','NDVI
```

- Select Feature above 0.6 correlation.

In [24]:
```
pd.set_option("display.max_rows",100)
corr = corr[(np.abs(corr['NDVI_mean'])>0.6) | (np.abs(corr['EVI_mean'])>0
corr
```

Out[24]:

state	region	crop		EVI_mean	NDVI_mean
MH	jethabhawda	kharif	soil_temperature_level_4_mean	-0.611169	-0.656061
			volumetric_soil_water_layer_4_mean	0.627993	0.613521
		rabi	volumetric_soil_water_layer_1_mean	0.737807	0.777476
			volumetric_soil_water_layer_2_mean	0.835457	0.879255
			volumetric_soil_water_layer_3_mean	0.877224	0.924978
			volumetric_soil_water_layer_4_mean	0.873363	0.920780
			dewpoint_depression	-0.858495	-0.905209
			surface_air_Temp_Diff	-0.718841	-0.763784
	mundhewadi	kharif	soil_temperature_level_4_mean	-0.666648	-0.692576
			volumetric_soil_water_layer_3_mean	0.625681	0.568772
			volumetric_soil_water_layer_4_mean	0.616920	0.532675
		rabi	temperature_2m_mean	-0.782975	-0.756373
			skin_temperature_mean	-0.825953	-0.814764
			soil_temperature_level_1_mean	-0.828818	-0.815588
			soil_temperature_level_2_mean	-0.826330	-0.809697
			soil_temperature_level_3_mean	-0.800639	-0.774155
			volumetric_soil_water_layer_2_mean	0.810662	0.826061
			volumetric_soil_water_layer_3_mean	0.842076	0.852765
			dewpoint_depression	-0.773677	-0.808108
			surface_air_Temp_Diff	-0.831518	-0.841218
			ratio_surface_air_temp	0.724422	0.726318
	tadklas	kharif	temperature_2m_mean	-0.633732	-0.597927
			skin_temperature_mean	-0.635747	-0.586711
			soil_temperature_level_1_mean	-0.678819	-0.633784
			soil_temperature_level_2_mean	-0.718544	-0.678716
			soil_temperature_level_3_mean	-0.729211	-0.703128
			soil_temperature_level_4_mean	-0.560743	-0.600949
			volumetric_soil_water_layer_3_mean	0.679666	0.634551
			dewpoint_depression	-0.621069	-0.590191
			surface_air_Temp_Diff	-0.617921	-0.539198
		rabi	temperature_2m_mean	-0.611591	-0.649650
			skin_temperature_mean	-0.691745	-0.734500

				EVI_mean	NDVI_mean
state	region	crop			
			soil_temperature_level_1_mean	-0.691253	-0.735641
			soil_temperature_level_2_mean	-0.685620	-0.730105
			soil_temperature_level_3_mean	-0.645672	-0.681623
			volumetric_soil_water_layer_2_mean	0.714079	0.768112
			volumetric_soil_water_layer_3_mean	0.814815	0.848517
			volumetric_soil_water_layer_4_mean	0.689735	0.713446
			dewpoint_depression	-0.786956	-0.832554
			surface_air_Temp_Diff	-0.764836	-0.803318
MP	ankia	rabi	temperature_2m_mean	-0.737209	-0.830130
			skin_temperature_mean	-0.699115	-0.796956
			soil_temperature_level_1_mean	-0.726158	-0.819518
			soil_temperature_level_2_mean	-0.758524	-0.843822
			soil_temperature_level_3_mean	-0.829401	-0.871911
			surface_pressure_mean	0.573292	0.678332
	chholya	rabi	temperature_2m_mean	-0.899947	-0.903519
			skin_temperature_mean	-0.891641	-0.905717
			soil_temperature_level_1_mean	-0.897818	-0.908432
			soil_temperature_level_2_mean	-0.900256	-0.900449
			soil_temperature_level_3_mean	-0.815868	-0.782452
			surface_pressure_mean	0.800828	0.814225
			dewpoint_depression	-0.736079	-0.794171
	kalyanpur	rabi	temperature_2m_mean	-0.892532	-0.885147
			skin_temperature_mean	-0.888958	-0.889377
			soil_temperature_level_1_mean	-0.885239	-0.882922
			soil_temperature_level_2_mean	-0.872958	-0.865073
			soil_temperature_level_3_mean	-0.747742	-0.716336
			surface_pressure_mean	0.763122	0.774025
			dewpoint_depression	-0.696972	-0.745905
			surface_air_Temp_Diff	-0.553081	-0.609246

Kharif Season Observations:

- Surface-Air Temperature Difference and Soil Temperature at Level 4 (mean) are negatively correlated with NDVI.
- Soil moisture volume is positively correlated with NDVI.
- This is expected — higher surface-air temperature differences indicate more heat stress on crops.
- Similarly, higher soil moisture supports healthier vegetation, leading to higher NDVI.

Rabi Season Observations:

- Surface-Air Temperature Difference and Soil Temperature at Level 4 (mean) are negatively correlated with NDVI.
- The Surface-Air Temperature Ratio is positively correlated, which suggests that when the surface temperature is closer to the dew point, vapor near the surface condenses, increasing moisture availability.
- Similarly, soil moisture volume shows a positive correlation with NDVI, indicating that higher moisture supports healthier crop growth.

In [26]:
```
selected_feature = corr.reset_index()['level_3'].unique()

selected_feature_str = '\n'.join(selected_feature)

print(f"selected_feature\n{selected_feature_str}")
```

```
selected_feature
soil_temperature_level_4_mean
volumetric_soil_water_layer_4_mean
volumetric_soil_water_layer_1_mean
volumetric_soil_water_layer_2_mean
volumetric_soil_water_layer_3_mean
dewpoint_depression
surface_air_Temp_Diff
temperature_2m_mean
skin_temperature_mean
soil_temperature_level_1_mean
soil_temperature_level_2_mean
soil_temperature_level_3_mean
ratio_surface_air_temp
surface_pressure_mean
```

Relative Comparison of NDVI

Compare low NDVI with high NDVI periods to analyze how climatic factors or changes contribute to a decrease in NDVI.

In [27]:
```
columns = ['NDVI_mean','EVI_mean'] + ['precipitation_mean','temperature_2
  'soil_temperature_level_4_mean', 'surface_pressure_mean','volumetric_so


columns = ['NDVI_mean','EVI_mean'] + list(selected_feature)


data_merged_ndvi_peak =  data_merged.groupby(['region','state','year','cr

    NDVI_peak = pd.NamedAgg(column = 'NDVI_mean',aggfunc = 'max') ,
    precipitation_mean = pd.NamedAgg(column = 'precipitation_mean',aggfun
     **{col:pd.NamedAgg(column = col,aggfunc = 'mean') for col in selecte

)

data_merged_ndvi_peak = data_merged_ndvi_peak.reset_index()
```

In [29]:
```
# data_merged_ndvi_peak[(data_merged_ndvi_peak['year'] < 2024) &
#                                  (data_merged_ndvi_peak.state == 'MH')  &
#                                  (data_merged_ndvi_peak.region == 'tadkla
#                                   (data_merged_ndvi_peak.NDVI_peak > 0.6)
```

In [30]:
```
columns = ['NDVI_peak', 'precipitation_mean'] + list(selected_feature)

columns_best = [col + '_best' for col in columns]
columns_diff = [col + '_diff' for col in columns]

##cross join
data_merged_ndvi_peak_compare =  data_merged_ndvi_peak.merge(data_merged_
# data_merged_nvdi_peak_compare  = data_merged_nvdi_peak_compare[data_mer
data_merged_ndvi_peak_compare = data_merged_ndvi_peak_compare.reset_index


data_diff =  -data_merged_ndvi_peak_compare[columns_best].values + data_m
df_diff = pd.DataFrame(data_diff,columns = columns_diff )

data_merged_ndvi_peak_compare = pd.concat([data_merged_ndvi_peak_compare


###filter out

columns_location = ['region', 'state', 'year', 'crop']

data_merged_ndvi_peak_compare = data_merged_ndvi_peak_compare[(data_merge
                                   (data_merged_ndvi_peak_compare['crop']

# data_merged_ndvi_peak_compare
```

In [32]:
```
# df.groupby( ['region', 'state', 'year', 'crop'])

data_merged_compare = []
data_merged_ndvi_peak_compare = data_merged_ndvi_peak_compare[data_merged

for _,grp in data_merged_ndvi_peak_compare.groupby(['region', 'state', 'y

    grp = grp.sort_values('NDVI_peak_diff',ascending = True)[columns_loca
    grp = grp.iloc[:3] # select top 3 most difference point

    if(grp.shape[0]==0):
        continue

    grp = grp.groupby(columns_location + ['NDVI_peak']).agg(

            year_comparision = pd.NamedAgg(column = "year_best", aggfunc
            NDVI_peak_compare_mean = pd.NamedAgg(column = "NDVI_peak_best

            **{col : pd.NamedAgg(column = col, aggfunc = 'mean' ) for col

    )

    data_merged_compare.append(grp)

data_merged_compare = pd.concat(data_merged_compare,axis=0).reset_index()
```

In [33]:
```
pd.set_option("display.max_rows",100)
pd.set_option("display.max_columns",100)
```

In [34]:
```
data_merged_compare
```

Out[34]:

	region	state	year	crop	NDVI_peak	year_comparision	NDVI_peak_compare_mean
0	ankia	MP	2008	kharif	0.413144	[2024, 2020, 2023]	0.798610
1	chholya	MP	2008	kharif	0.362551	[2009, 2022, 2012]	0.774188
2	chholya	MP	2008	rabi	0.403128	[2020, 2022, 2021]	0.684985
3	chholya	MP	2009	rabi	0.468439	[2020, 2022]	0.706330
4	chholya	MP	2010	rabi	0.496936	[2020]	0.725693
5	chholya	MP	2011	rabi	0.477868	[2020, 2022]	0.706330
6	chholya	MP	2012	rabi	0.439636	[2020, 2022, 2021]	0.684985
7	chholya	MP	2013	rabi	0.483926	[2020, 2022]	0.706330
8	kalyanpur	MP	2008	kharif	0.365796	[2023, 2009, 2010]	0.834287
9	kalyanpur	MP	2013	kharif	0.518719	[2023, 2009, 2010]	0.834287
10	kalyanpur	MP	2016	kharif	0.625774	[2023, 2009, 2010]	0.834287
11	kalyanpur	MP	2018	kharif	0.513593	[2023, 2009, 2010]	0.834287
12	kalyanpur	MP	2019	kharif	0.577027	[2023, 2009, 2010]	0.834287
13	mundhewadi	MH	2009	kharif	0.371694	[2024]	0.589234
14	mundhewadi	MH	2011	kharif	0.383520	[2024]	0.589234
15	mundhewadi	MH	2012	kharif	0.352186	[2024]	0.589234
16	tadklas	MH	2015	kharif	0.577370	[2024, 2022, 2023]	0.834395

The above table presents a comparison across different years to identify which climatic variables may be contributing to a decline in NDVI.

Cross Verify some of the facts

Year	State	Region	What Happened(referred from above table)	Source to Verify
2013	MP	Kalyanpur	Excessive Rainfall during Kharif season	In 2013, Madhya Pradesh did experience excessive rainfall during the monsoon season, which led to crop damage in some areas
2016	MP	Kalyanpur	Excessive Rainfall during Kharif season	https://reliefweb.int/report/india/casa-report-floods-situation-madhya-pradesh)
2008	MP	chholya	Excessive Heat During Rabi (+2 deg)	https://imdpune.gov.in/library/public/Disastrous%20Weather%20Events%202008.pdf

In [36]:

```
# corr[corr.level_3 == 'precipitation_mean']
```