# Etude Environnementale [Axe spatio-temporel]

Cette Etude investigera les questions suivantes: • Est ce qu'il y a une relation entre les types de routes ,ou les conditions de conduite , et le degré d'occurence des sinistres automobiles corporels? • Comment varie les conditions d'accidents parmi les communes ? J'esserai de répondre à ces questions en étudiant les relations entre les accidents et les cas fatales et: • Catégorie de route • Conditions lumière • Conditions météo • Conditions surfaces de routes

Plan: *Etudier les collisions pendant toute l'année et pendant la journée.* Investiger les données groupés par commune et identifier les correlations entre les conditions environnementales et le taux d'accidents. Ceci dit , un modèle de regression linéaire sera utilisé pour décrire cette relation. *Identifion les clusters de communes avec des conditons environnementales similaires pour ainsi évaluer leurs propagations sur tout le pays et comment ceci est comparé avec le modèle.

In [4]:

```
import numpy as np
import pandas as pd
#import geopandas as gpd
from matplotlib import pyplot as plt
from matplotlib import dates as dates
from matplotlib.ticker import NullFormatter
import seaborn as sns
from sklearn.preprocessing import quantile_transform, MinMaxScaler
from sklearn.cluster import KMeans
from sklearn.metrics import pairwise_distances_argmin_min
from scipy import stats
```

In [6]:

```
crct = pd.read_csv('caracteristiques-2017.csv',encoding='latin-1')
veh = pd.read_csv('vehicules-2017.csv',encoding='latin-1')
usager = pd.read_csv('usagers-2017.csv',encoding='latin-1')
lieux = pd.read_csv('lieux-2017.csv',encoding='latin-1',low_memory=False)
```

# Data Preparation

In [7]:

```
crct.head()
```

Out[7]:

| | Num_Acc | an | mois | jour | hrmn | lum | agg | int | atm | col | com | adr | gps | lat | long | dep |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | 1 | 11 | 1820 | 5 | 2 | 1 | 1.0 | 1.0 | 477 | rue nationale | M | 5051326.0 | 292191.0 | 590 |
| **1** | 201700000002 | 17 | 2 | 13 | 1630 | 1 | 2 | 3 | 1.0 | 3.0 | 5 | 5 rue sonneville | M | 5053611.0 | 295314.0 | 590 |
| **2** | 201700000003 | 17 | 3 | 7 | 1150 | 1 | 2 | 9 | 1.0 | 5.0 | 52 | rue Jules Guesde | M | 5052174.0 | 288786.0 | 590 |
| **3** | 201700000004 | 17 | 4 | 22 | 1300 | 1 | 2 | 1 | 1.0 | 6.0 | 5 | 46 rue Sonneville | M | 5053723.0 | 295700.0 | 590 |
| **4** | 201700000005 | 17 | 5 | 20 | 1230 | 1 | 2 | 1 | 1.0 | 2.0 | 11 | Rue roger salengro | M | 5052999.0 | 293798.0 | 590 |

In [8]:

```
l = lieux.drop(['voie','v1','v2','circ','pr','pr1','vosp','prof','plan','lartpc','larrout','infra']
,1)
ac = crct.merge(l,on='Num_Acc')
```

In [9]:

```
u = usager.drop(['place','catu','sexe','trajet','secu','locp','actp','etatp','an_nais','num_veh'],1
)
nu= u.drop_duplicates()
nu = nu.drop_duplicates(subset='Num_Acc', keep='first', inplace=False)
```

```
nu
acc_env = ac.merge(nu,on='Num_Acc')
acc_env.columns
```

Out[9]:

```
Index(['Num_Acc', 'an', 'mois', 'jour', 'hrmn', 'lum', 'agg', 'int', 'atm',
       'col', 'com', 'adr', 'gps', 'lat', 'long', 'dep', 'catr', 'nbv', 'surf',
       'situ', 'env1', 'grav'],
      dtype='object')
```

In [10]:

```
acc_env=acc_env.rename(columns={"lum":"Conditions_lumière","grav":"Gravité_accident","atm":"Atmosph
ere","com":"Commune","int":"Intersections","col":"Collision","surf":"Conditions_Surface","lat":"Lat
itude","long":"Longitude","agg":"Agglomération","catr":"Catégorie_Route","dep":"Département"})
env_data=acc_env.drop(['situ','env1','nbv','gps','adr','Collision','Intersections'],1)
```

In [10]:

```
print(env_data.isnull().sum())
```

```
Num_Acc                0
an                     0
mois                   0
jour                   0
hrmn                   0
Conditions_lumière     0
Agglomération          0
Atmosphere            13
Commune                0
Latitude            7731
Longitude           7731
Département            0
Catégorie_Route        0
Conditions_Surface   465
Gravité_accident       0
dtype: int64
```

In [15]:

```
```

In [11]:

```
env_data.head()
```

Out[11]:

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | Agglomération | Atmosphere | Commune | Latitude | Longitude | Départeme |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | 1 | 11 | 1820 | 5 | 2 | 1.0 | 477 | 5051326.0 | 292191.0 | 5 |
| **1** | 201700000002 | 17 | 2 | 13 | 1630 | 1 | 2 | 1.0 | 5 | 5053611.0 | 295314.0 | 5 |
| **2** | 201700000003 | 17 | 3 | 7 | 1150 | 1 | 2 | 1.0 | 52 | 5052174.0 | 288786.0 | 5 |
| **3** | 201700000004 | 17 | 4 | 22 | 1300 | 1 | 2 | 1.0 | 5 | 5053723.0 | 295700.0 | 5 |
| **4** | 201700000005 | 17 | 5 | 20 | 1230 | 1 | 2 | 1.0 | 11 | 5052999.0 | 293798.0 | 5 |

In [12]:

```
env_data['Conditions_Surface'].fillna(env_data.Conditions_Surface.mode()[0],inplace=True)
env_data['Atmosphere'].fillna(env_data.Atmosphere.mode()[0],inplace=True)
```

**Clarifier les noms des modalités d'après le descriptif des variables**

In [13]:

```
env_data["Gravité_accident"].replace([1,2,3,4],["Non Grave","Fatale","Sévère","Léger "], inplace=True)
env_data["Conditions_lumière"].replace([1,2,3,4,5],["Plein jour","Crépuscule ou aube","Nuit sans éclairage public","Nuit avec éclairage public non allumé","Nuit avec éclairage public allumé"], inplace=True)
env_data["Agglomération"].replace([1,2],["Hors agglomération","En agglomération"], inplace=True)
env_data["Atmosphere"].replace([1,2,3,4,5,6,7,8,9],["Normale","Pluie légère","Pluie forte","Neige-grêlé","Brouillard fumée","Vent fort-tempête","Temps eblouissant","Temps couvert","Autre"], inplace=True)
env_data["Agglomération"].replace([1,2],["Hors agglomération","En agglomération"], inplace=True)
env_data["Catégorie_Route"].replace([1,2,3,4,5,6,9],["Autoroute","Route Nationale","Route Departementale","Voie Communale","Hors réseau public","ParcStationOuvCirPub","Autre"], inplace=True)
env_data["Conditions_Surface"].replace([1,2,3,4,5,6,7,8,9],["Normale","Mouillée","Flaques","Inondée","Enneigée","Boue","Verglacée","Corps gras-huile","Autre"], inplace=True)
```

In [ ]:

```
```

In [14]:

```
env_data.head()
```

Out[14]:

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | Agglomération | Atmosphere | Commune | Latitude | Longitude | Départeme |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | 1 | 11 | 1820 | Nuit avec éclairage public allumé | En agglomération | Normale | 477 | 5051326.0 | 292191.0 | 5 |
| **1** | 201700000002 | 17 | 2 | 13 | 1630 | Plein jour | En agglomération | Normale | 5 | 5053611.0 | 295314.0 | 5 |
| **2** | 201700000003 | 17 | 3 | 7 | 1150 | Plein jour | En agglomération | Normale | 52 | 5052174.0 | 288786.0 | 5 |
| **3** | 201700000004 | 17 | 4 | 22 | 1300 | Plein jour | En agglomération | Normale | 5 | 5053723.0 | 295700.0 | 5 |
| **4** | 201700000005 | 17 | 5 | 20 | 1230 | Plein jour | En agglomération | Normale | 11 | 5052999.0 | 293798.0 | 5 |

In [ ]:

```
```

In [15]:

```
usagers = pd.read_csv('usagers-2017-préparé.csv',encoding="utf-16")
```

In [16]:

```
#Ajouter données usager dans la table principale
fatalitées = pd.get_dummies(usagers['Gravité_accident'])
fatalitées = fatalitées[['Tué','Blessé hospitalisé']]
fatalitées = fatalitées[(fatalitées['Tué']==1)|(fatalitées['Blessé hospitalisé']==1)]
usagerCount = pd.concat([usagers['Num_Acc'], fatalitées], axis=1)
usagerCount.dropna(inplace=True)
usagerCount = usagerCount.groupby('Num_Acc').sum()
acc_env = env_data.join(usagerCount,on='Num_Acc')
acc_env['Nombre_Accident']=1
acc_env.fillna(value=0,inplace=True)

new_df = acc_env[(acc_env['Conditions_lumière']!='Data missing or out of range') &
              (acc_env['Atmosphere']!='Data missing or out of range') &
              (acc_env['Atmosphere']!='Unknown') &
              (acc_env['Conditions_Surface']!='Data missing or out of range')]

#Créer la table de dummies pour les colonnes en question
dummies = pd.get_dummies(new_df[['Conditions_lumière','Atmosphere',
                                 'Conditions_Surface']])

#Reset index
dummies.reset_index(inplace=True)
```

```
dummies.drop('index',axis=1,inplace=True)

#Add row for national totals
dummySum = dummies.sum(axis=0)
dummies = dummies.append(dummySum.transpose(),ignore_index=True)
dummies.loc[len(dummies)-1,'totNat'] = 'Total National'
dummies.fillna(value=0,inplace=True)
```

In [17]:

```
new_df.head()
```

Out[17]:

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | Agglomération | Atmosphere | Commune | Latitude | Longitude | Départeme |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | 1 | 11 | 1820 | Nuit avec éclairage public allumé | En agglomération | Normale | 477 | 5051326.0 | 292191.0 | 5 |
| **1** | 201700000002 | 17 | 2 | 13 | 1630 | Plein jour | En agglomération | Normale | 5 | 5053611.0 | 295314.0 | 5 |
| **2** | 201700000003 | 17 | 3 | 7 | 1150 | Plein jour | En agglomération | Normale | 52 | 5052174.0 | 288786.0 | 5 |
| **3** | 201700000004 | 17 | 4 | 22 | 1300 | Plein jour | En agglomération | Normale | 5 | 5053723.0 | 295700.0 | 5 |
| **4** | 201700000005 | 17 | 5 | 20 | 1230 | Plein jour | En agglomération | Normale | 11 | 5052999.0 | 293798.0 | 5 |

In [18]:

```
new_df.to_csv('acc_env.csv',encoding="utf-16",index=False)
```

In [ ]:

```
#préparer la date avec le script R date qui sera nécessaire pour les visualisations
```

In [18]:

```
date_df = pd.read_csv('new_env.csv',encoding='latin1')
date_df=date_df.drop(['weekdayshours','an','mois','jour','hrmn','Conditions_lumiÃ.re','AgglomÃ.rati
on','Atmosphere','Commune','Latitude'
,'Conditions_Surface','GravitÃ._accident','TuÃ.','BlessÃ..hospitalisÃ.','Nombre_Accident','Longituc
e','DÃ.partement'
,'CatÃ.gorie_Route'],1)
```

In [19]:

```
df_final = new_df.merge(date_df,on='Num_Acc')
df_final.head()
```

Out[19]:

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | Agglomération | Atmosphere | Commune | Latitude | ... | Conditions_Surfac |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | 1 | 11 | 1820 | Nuit avec éclairage public allumé | En agglomération | Normale | 477 | 5051326.0 | ... | Normal |
| **1** | 201700000002 | 17 | 2 | 13 | 1630 | Plein jour | En agglomération | Normale | 5 | 5053611.0 | ... | Normal |
| **2** | 201700000003 | 17 | 3 | 7 | 1150 | Plein jour | En agglomération | Normale | 52 | 5052174.0 | ... | Normal |
| **3** | 201700000004 | 17 | 4 | 22 | 1300 | Plein jour | En agglomération | Normale | 5 | 5053723.0 | ... | Normal |
| **4** | 201700000005 | 17 | 5 | 20 | 1230 | Plein jour | En | Normale | 11 | 5052999.0 | | Normal |

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | agglomération Agglomération | Atmosphere | Commune | Latitude | ... | Conditions_Surfac |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

5 rows × 23 columns

In [20]:

```
df_final["wday"].replace(["lun\.","mar\.","mer\.","jeu\.","ven\.","sam\.","dim\."],
                                 ["Lundi","Mardi","Mercredi","Jeudi","Vendredi","Samedi","Dimanche
,], inplace=True)
```

In [21]:

```
df_final["mois"].replace([1,2,3,4,5,6,7,8,9,10,11,12],
    ["Janvier","Février","Mars","Avril","Mai","Juin","Juillet","Aout","Septembre","Octobre","Novemb
re","Décembre"], inplace=True)
```

In [ ]:

```
##########################################################################################################
#########################
```

# Data Analysis

In [22]:

```
df_final.head()
```

Out[22]:

| | Num_Acc | an | mois | jour | hrmn | Conditions_lumière | Agglomération | Atmosphere | Commune | Latitude | ... | Conditions_Surfa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 201700000001 | 17 | Janvier | 11 | 1820 | Nuit avec éclairage public allumé | En agglomération | Normale | 477 | 5051326.0 | ... | Norm |
| **1** | 201700000002 | 17 | Février | 13 | 1630 | Plein jour | En agglomération | Normale | 5 | 5053611.0 | ... | Norm |
| **2** | 201700000003 | 17 | Mars | 7 | 1150 | Plein jour | En agglomération | Normale | 52 | 5052174.0 | ... | Norm |
| **3** | 201700000004 | 17 | Avril | 22 | 1300 | Plein jour | En agglomération | Normale | 5 | 5053723.0 | ... | Norm |
| **4** | 201700000005 | 17 | Mai | 20 | 1230 | Plein jour | En agglomération | Normale | 11 | 5052999.0 | ... | Norm |

5 rows × 23 columns

In [23]:

```
#Configurer format date
df_final['date'] = pd.to_datetime(df_final['date'], format='%Y/%m/%d').dt.date
#df_final['hrmn'] = pd.to_datetime(acc16['hrmn'], format='%H:%M').dt.time
#df_final['Month'] = pd.DatetimeIndex(acc16['Date']).month
```

In [ ]:

```

```

In [24]:

```
jours = ['Lundi','Mardi','Mercredi','Jeudi','Vendredi','Samedi','Dimanche']
```

In [25]:

```
dummies = pd.concat([df_final[['Commune','Nombre_Accident',
                               'Blessé hospitalisé','Tué','date',
                               'wday','hour']], dummies],axis=1)
```

In [26]:

```
df_final["Conditions_Surface"].replace([0],["Boue"], inplace=True)
```

In [27]:

```
################## Prepare Initial visualisation ##############################

#Calculer la distribution des accidents durant toute l'année
#Grouper les accidents par date
byDate = df_final[['date','Num_Acc']].groupby('date').count()
byDate['date'] = byDate.index

#Identifier les valeurs aberrantes
dailyAccMean = byDate['Num_Acc'].mean()
dailyAccSD = byDate['Num_Acc'].std()

check_high = dailyAccMean + 2*dailyAccSD
check_low = dailyAccMean - 2*dailyAccSD
byDate['isOutlier'] = (byDate['Num_Acc'] > check_high)|(byDate['Num_Acc'] < check_low)
byDate['pltColour'] = '#B9BCC0'
byDate.loc[byDate['isOutlier'] == True, 'pltColour'] = 'r'

#Calculer la distribution des accidents durant la journée
byHour = df_final[['hour','Num_Acc']].groupby('hour').count()
byHour['Num_Acc'] = byHour['Num_Acc'].apply(lambda x: x/366) # Transformer total à valeur par jour

#Grouper les accidents pour chaque catégorie de route où ils ont occuré
byRoadType = df_final[['Nombre_Accident','Catégorie_Route','Blessé hospitalisé','Tué']].groupby('C
atégorie_Route').sum()
byRoadType.reset_index(inplace=True)
byRoadType
```

Out[27]:

| | Catégorie_Route | Nombre_Accident | Blessé hospitalisé | Tué |
|---|---|---|---|---|
| **0** | Autoroute | 5692 | 1884.0 | 283.0 |
| **1** | Autre | 744 | 377.0 | 51.0 |
| **2** | Hors réseau public | 68 | 38.0 | 2.0 |
| **3** | ParcStationOuvCirPub | 476 | 240.0 | 16.0 |
| **4** | Route Départementale | 21900 | 14767.0 | 2262.0 |
| **5** | Route Nationale | 3974 | 2088.0 | 312.0 |
| **6** | Voie Communale | 27847 | 9599.0 | 674.0 |

In [28]:

```
############### Etudier les données par date ######################################

#Calculer la distribution des accidents pendant tous les jours de la semaine

#pour toute l'année , plus spécifiquement juin et décembre
byHourDay = df_final[['hour','wday','Nombre_Accident','Blessé hospitalisé','Tué']].groupby(['hour'
,'wday']).sum().reset_index()
byHourDayJune = df_final.loc[df_final['mois'] == "Juin",['hour','wday','Nombre_Accident','Blessé ho
spitalisé','Tué']].groupby(['hour','wday']).sum().reset_index()
byHourDayDec = df_final.loc[df_final['mois'] == "Décembre",['hour','wday','Nombre_Accident','Blessé
hospitalisé','Tué']].groupby(['hour','wday']).sum().reset_index()
```

In [29]:

```
AccbyHourDay = byHourDay.pivot(index='hour',columns='wday',values='Nombre_Accident')/366
AccbyHourDay = AccbyHourDay[jours]
```

In [30]:

```
AccbyHourDayJune = byHourDayJune.pivot(index='hour',columns='wday',values='Nombre_Accident')/30
AccbyHourDayJune = AccbyHourDayJune[jours]
```

In [31]:

```
AccbyHourDayDec = byHourDayDec.pivot(index='hour',columns='wday',values='Nombre_Accident')/31
AccbyHourDayDec = AccbyHourDayDec[jours]
```

In [32]:

```
SeriousbyHourDay = byHourDay.pivot(index='hour',columns='wday',values='Blessé hospitalisé')
SeriousbyHourDay = SeriousbyHourDay[jours]
```

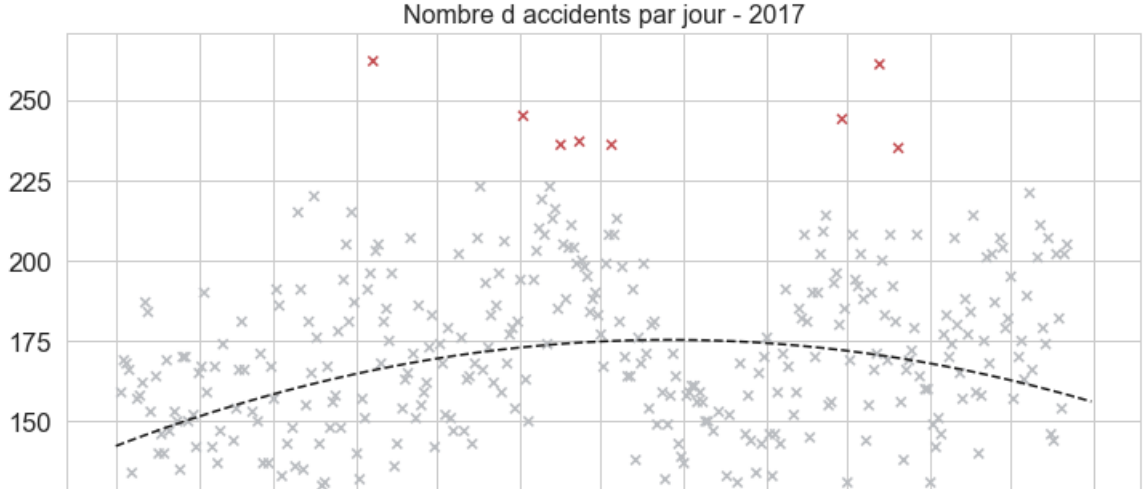
In [33]:

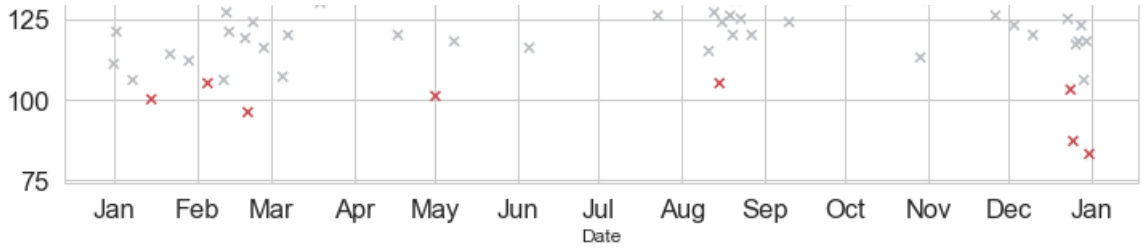
```
DeathbyHourDay = byHourDay.pivot(index='hour',columns='wday',values='Tué')
DeathbyHourDay = DeathbyHourDay[jours]
```

## Distribution des Accidnets : Axe temporel

In [83]:

```
sns.set_style('whitegrid')
fig, ax = plt.subplots(2,1, figsize = (12,16))
plotDates = dates.date2num(byDate['date'])
plt.style.use('ggplot')
months = dates.MonthLocator()  # chaque mois
monthsFmt = dates.DateFormatter('%b')

#regréssion linéaire  sur les données regroupées par date
pCoeff = np.polyfit(plotDates, byDate['Num_Acc'], 2)
regLine = np.poly1d(pCoeff)



#plot par jour
ax[0].scatter(plotDates, byDate['Num_Acc'],marker= 'x', c= byDate['pltColour'])
ax[0].plot(plotDates, regLine(plotDates), 'k--')
ax[0].xaxis.set_major_locator(months)
ax[0].xaxis.set_major_formatter(monthsFmt)
ax[0].set_title('Nombre d accidents par jour - 2017', fontsize=16)
ax[0].set_xlabel('Date')

#plot par heure
ax[1].plot(byHour.index, byHour['Num_Acc'], c='b')
ax[1].set_title('Nombre moyen quotidien d accidents par heure - 2017', fontsize=16)
ax[1].set_xlabel('Heure de la journée')
plt.savefig('Time.png',bbox_inches='tight')
```





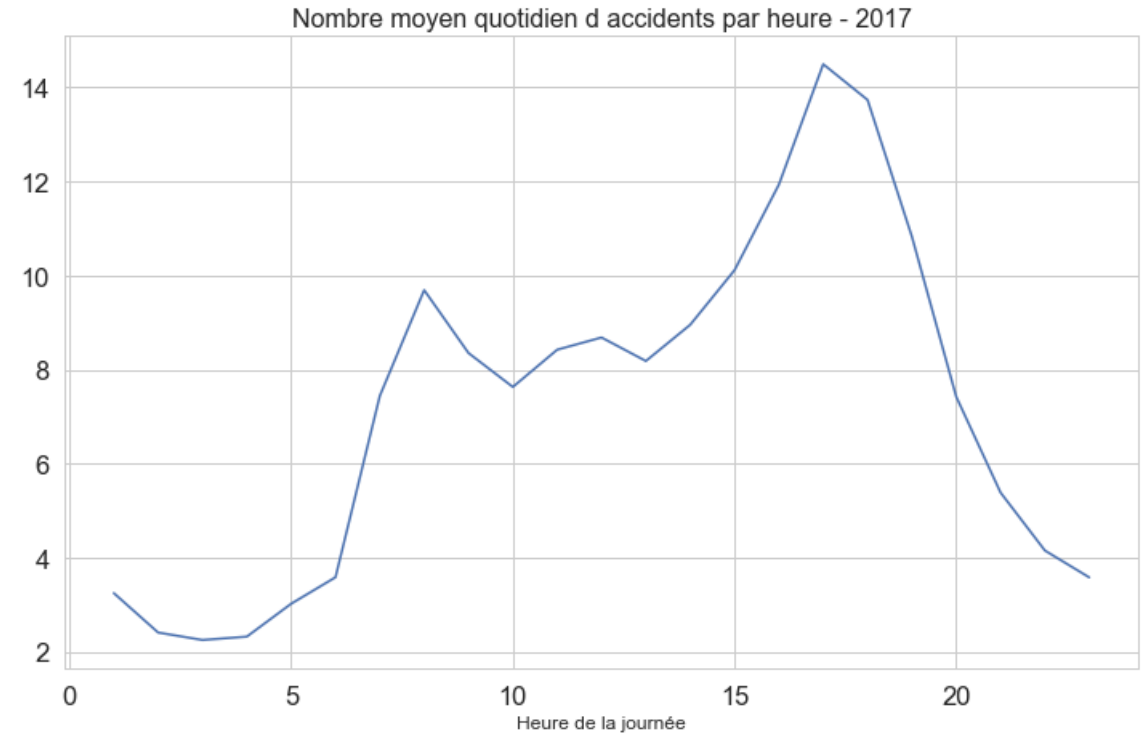




Figure 1: Distribution des accidents de la route en France pendant 2017. Les valeurs aberrantes (>2sd de la moyenne) sont marqués en rouge.

*Les Accidents ont été regroupés par date et leurs distribution durant l'année est visualisée dans cette figure. On remarque qu'après l'été le nombre d'accidents baisse fortement et rebondit en début d'hiver. Ce qui montre que l'automne est la saison la moins dangereuse de l'année. Un point d'interet frappant si on focalise sur les 3 valeurs aberrantes positionnées en fin Décembre. Ce sont les 3 jours de l'année où il y a le moins d'accidents : Noel, Boxing Day, et le réveillon.

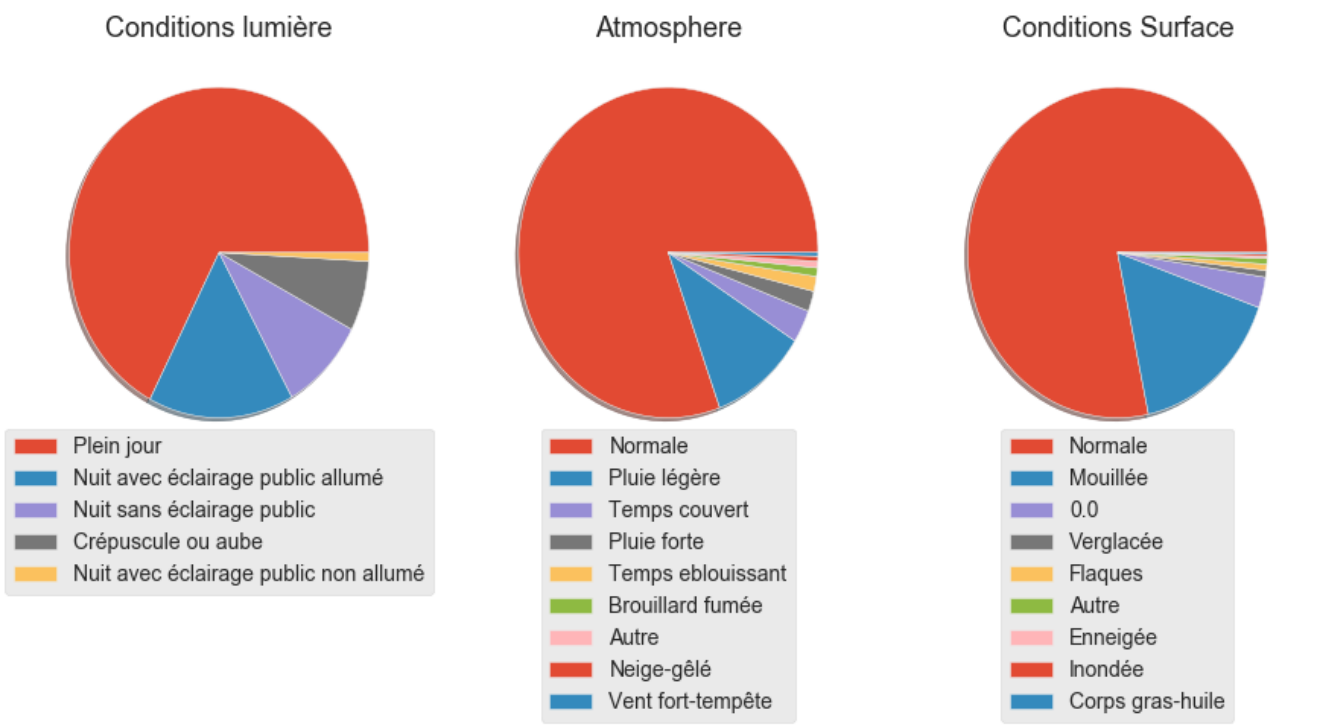
Figure 2:Distribution pendant les heures de la journée

*Cette figue montre que généralement les heures où il est plus probable d'avoir le plus d'accidents sont aux environs de 8h et de 17h ce qui n'est pas surprenant du au fiat que ce sont les heures d'entrée et sortie de travail présentant les plus de véhicules sur les routes.

## Distribution des Accidents : Axe Spatial

In [35]:

```
#Plot summary du nombre d'accidents toutes les valeurs de chaque conditon environnemetale
fig4,ax4 = plt.subplots(1,3,figsize=(15,5))
ax4[0].pie(df_final['Conditions_lumière'].value_counts(), shadow=True)
ax4[0].set_title('Conditions lumière',fontsize=18)
pieleg0 = ax4[0].legend(labels=env_data['Conditions_lumière'].value_counts().index,bbox_to_anchor=(
0.5,0.1), fontsize=14,loc="upper center")
ax4[1].pie(df_final['Atmosphere'].value_counts(), shadow=True)
ax4[1].set_title('Atmosphere',fontsize=18)
pieleg1 = ax4[1].legend(labels=env_data['Atmosphere'].value_counts().index,bbox_to_anchor=(0.5,0.1)
, fontsize=14,loc="upper center")
ax4[2].pie(df_final['Conditions_Surface'].value_counts(), shadow=True)
ax4[2].set_title('Conditions Surface',fontsize=18)
pieleg2 = ax4[2].legend(labels=env_data['Conditions_Surface'].value_counts().index,bbox_to_anchor=(
0.5,0.1), fontsize=14,loc="upper center")
#plt.savefig('Condition Pies.jpg', bbox_extra_artists=(pieleg0,pieleg1,pieleg2),
bbox_inches='tight')
#plt.tight_layout()
```




*Toutes les conditions environnementales ont montré une meme distirbution d'accidents, avec une catégorie augementant à 70-85% d'observations, une deuxième catégorie de 10-25%, et le reste est couvert par les conditions les plus rares. Ceci est tout à fait attendu car il est connu que généralement en France le temps est clair et sec, mais parfois pluvieux, et la circulation est plus courante en pleine journée.

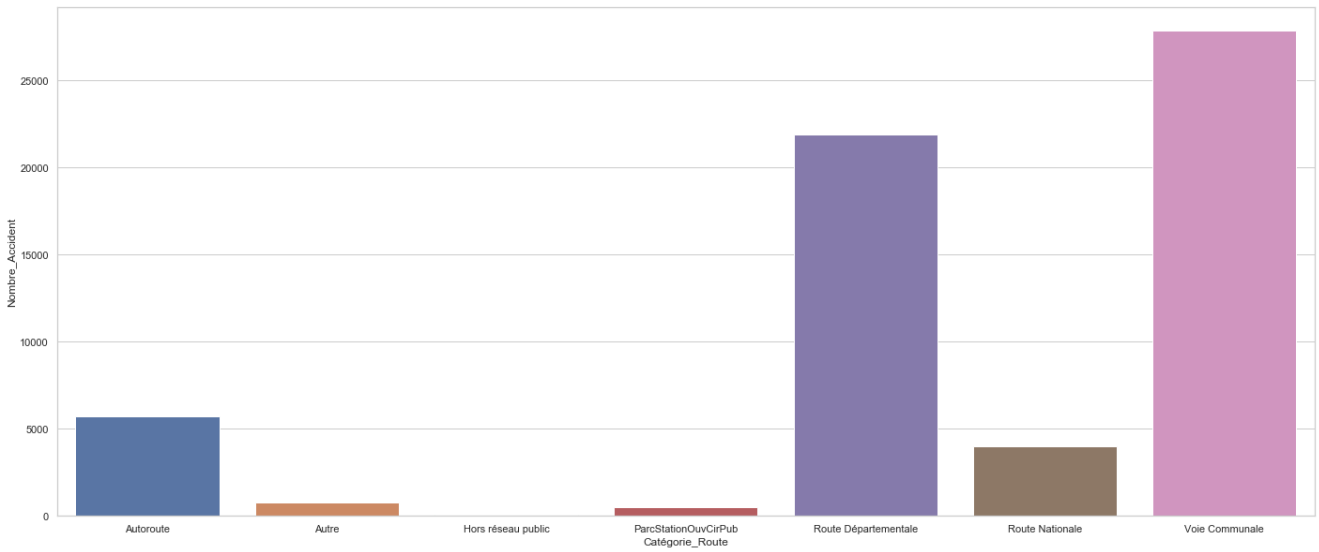
## Visualisations Par catégorie de route

In [37]:

```
plt.figure(figsize=(24,10))
sns.set(style="whitegrid")
#Accidents
sns.barplot(x='Catégorie_Route', y='Nombre_Accident', data=byRoadType)
```

Out[37]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f595f75ba8>
```

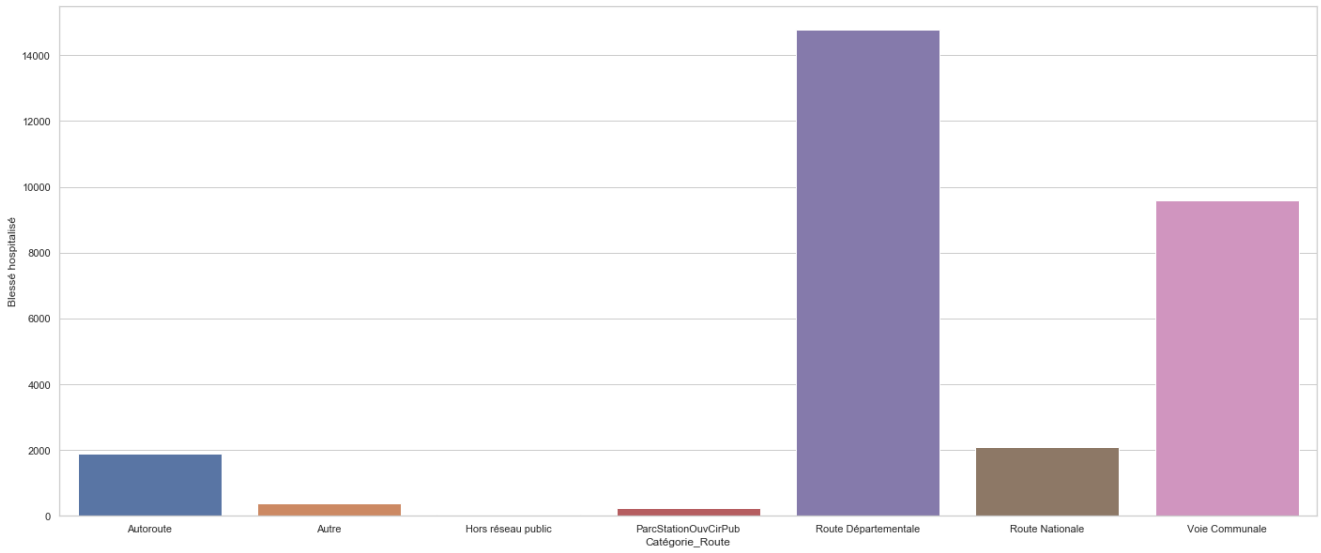



In [38]:

```
plt.figure(figsize=(24,10))
sns.set(style="whitegrid")
sns.barplot(x='Catégorie_Route', y='Blessé hospitalisé', data=byRoadType)
```

Out[38]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f595f99b00>
```

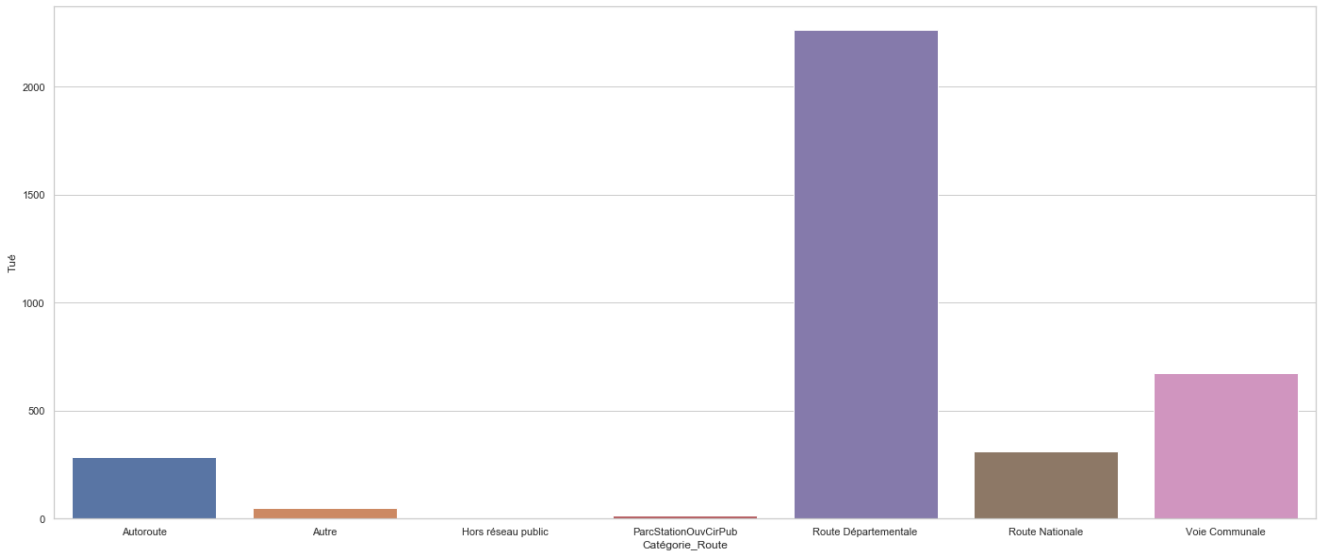



In [39]:

```
plt.figure(figsize=(24,10))
sns.set(style="whitegrid")
sns.barplot(x='Catégorie_Route', y='Tué', data=byRoadType)
```

Out[39]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1f59674dc88>
```




*Les Accidents, Cas graves et les cas mortels ont été regroupés par la catégorie de routes où ils ont couru et repréentés dans les histogrammes ci-dessus. On constate que la voie communale est la plus sensible aux accidents mais quad il s'agit des degrés sévères d'accident c'est la route départmentale qui est la plus dangereuse .

## Groupement et normisation par Commune

In [36]:

```
population = pd.read_csv(r"populat.csv",sep=";")
population.head()
```

Out[36]:

| Code | Code | | | | | Altitude | | | |
|---|---|---|---|---|---|---|---|---|---|

| | Code INSEE | Code Postal | Commune | Département | Région | Statut | Altitude Moyenne | Superficie | Population | geo_point_2d | geo_shap |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | INSEE | Postal | Commune | Département | Région | Statut | Moyenne | Superficie | Population | geo_point_2d | geo_shap |
| 0 | 32460 | 32720 | VERGOIGNAN | GERS | MIDI-PYRENEES | Commune simple | 126.0 | 1056.0 | 0.3 | 43.7235746425, -0.188266221507 | {"type "Polygor "coordinates [[[-0.19884 |
| 1 | 51141 | 51240 | LA CHAUSSEE-SUR-MARNE | MARNE | CHAMPAGNE-ARDENNE | Commune simple | 130.0 | 2240.0 | 0.7 | 48.8433156105, 4.54286173009 | {"type "Polygor "coordinates [[[4.504753 |
| 2 | 77130 | 77580 | COULOMMES | SEINE-ET-MARNE | ILE-DE-FRANCE | Commune simple | 136.0 | 371.0 | 0.4 | 48.8919104938, 2.92942534432 | {"type "Polygor "coordinates [[[2.940606 |
| 3 | 63379 | 63460 | SAINT-MYON | PUY-DE-DOME | AUVERGNE | Commune simple | 365.0 | 556.0 | 0.4 | 45.9871537427, 3.12955448011 | {"type "Polygor "coordinates [[[3.137773 |
| 4 | 62050 | 62770 | AUCHY-LES-HESDIN | PAS-DE-CALAIS | NORD-PAS-DE-CALAIS | Commune simple | 72.0 | 986.0 | 1.7 | 50.4085719795, 2.09530419017 | {"type "Polygor "coordinates [[[2.105157 |

In [ ]:

In [37]:

```
#Grouper par Commune
parCommune = dummies.groupby('Commune').sum()
#Ajouter les données de populaiton pour les communes
parCommune = parCommune.join(population,how='left')
parCommune.drop('hour',axis=1,inplace=True)

#Claculé degré d'accidents /1000 résidents
parCommune['AccPerKPerson'] = (parCommune['Nombre_Accident']/parCommune['Population'])*1000
parCommune['GravePerKPerson'] = (parCommune['Blessé hospitalisé']/parCommune['Population'])*1000
parCommune['MortPerKPerson'] = (parCommune['Tué']/parCommune['Population'])*1000

# Liste des valeurs des variables de conditions environnementales qu'on veut investiger

lumCols = ['Conditions_lumière_Crépuscule ou aube',
       'Conditions_lumière_Nuit avec éclairage public allumé',
       'Conditions_lumière_Nuit avec éclairage public non allumé',
       'Conditions_lumière_Nuit sans éclairage public',
       'Conditions_lumière_Plein jour']

atmCols = ['Atmosphere_Brouillard fumée', 'Atmosphere_Neige-gêlé',
       'Atmosphere_Normale', 'Atmosphere_Pluie forte',
       'Atmosphere_Pluie légère', 'Atmosphere_Temps couvert',
       'Atmosphere_Temps eblouissant', 'Atmosphere_Vent fort-tempête']

surfCols = ['Conditions_Surface_Autre',
       'Conditions_Surface_Boue', 'Conditions_Surface_Corps gras-huile',
       'Conditions_Surface_Enneigée', 'Conditions_Surface_Flaques',
       'Conditions_Surface_Inondée', 'Conditions_Surface_Mouillée',
       'Conditions_Surface_Normale', 'Conditions_Surface_Verglacée']

toutesCols = ['Conditions_lumière_Crépuscule ou aube',
       'Conditions_lumière_Nuit avec éclairage public allumé',
       'Conditions_lumière_Nuit avec éclairage public non allumé',
       'Conditions_lumière_Nuit sans éclairage public',
       'Conditions_lumière_Plein jour', 'Atmosphere_Autre',
       'Atmosphere_Brouillard fumée', 'Atmosphere_Neige-gêlé',
       'Atmosphere_Normale', 'Atmosphere_Pluie forte',
       'Atmosphere_Pluie légère', 'Atmosphere_Temps couvert',
       'Atmosphere_Temps eblouissant', 'Atmosphere_Vent fort-tempête',
       'Conditions_Surface_Autre',
       'Conditions_Surface_Boue', 'Conditions_Surface_Corps gras-huile',
       'Conditions_Surface_Enneigée', 'Conditions_Surface_Flaques',
       'Conditions_Surface_Inondée', 'Conditions_Surface_Mouillée',
       'Conditions_Surface_Normale', 'Conditions_Surface_Verglacée']

parCommuneProp = parCommune[toutesCols].copy()
for col in parCommuneProp.columns.values:
```

```
    for row in parCommuneProp.index:
        parCommuneProp.loc[row,col] =
parCommuneProp.loc[row,col]/parCommune.loc[row,'Nombre_Accident']

scaler = MinMaxScaler(feature_range=(0,1),copy=True)

#Normaliser les valuers avec le quantile transform
parCommuneNorm = pd.DataFrame(data=quantile_transform(parCommuneProp.copy()), index=parCommuneProp
.index, columns=parCommuneProp.columns.values).copy()
```

In [ ]:

```
```

In [38]:

```
parCommune.head()
```

Out[38]:

| Commune | Nombre_Accident | Blessé hospitalisé | Tué | Conditions_lumière_Crépuscule ou aube | Conditions_lumière_Nuit avec éclairage public allumé | Conditions_lumière_Nuit avec éclairage public non allumé | Conds |
|---|---|---|---|---|---|---|---|
| **1.0** | 382.0 | 186.0 | 20.0 | 28 | 63 | 3 | |
| **2.0** | 222.0 | 82.0 | 13.0 | 14 | 25 | 2 | |
| **3.0** | 187.0 | 112.0 | 13.0 | 18 | 24 | 0 | |
| **4.0** | 555.0 | 187.0 | 28.0 | 35 | 101 | 5 | |
| **5.0** | 408.0 | 162.0 | 12.0 | 28 | 42 | 7 | |

5 rows × 47 columns

In [ ]:

```
```

In [ ]:

```
```

## Segmentation sur les communes

In [39]:

```
####### Essayez de trouver des clusters sensibles aux differents conditions environnementales ####
###############

#Segementer les communes par les differents attributs
cluster1 = KMeans(n_clusters=3).fit(parCommuneProp[toutesCols])
cluster2 = KMeans(n_clusters=3).fit(parCommuneProp[lumCols])
cluster3 = KMeans(n_clusters=3).fit(parCommuneProp[atmCols])
cluster4 = KMeans(n_clusters=3).fit(parCommuneProp[surfCols])

#Ajouter les clusters à la table parCommune
```

```
#Ajouter les clusters à la table parCommune
parCommune['cluster1'] = cluster1.labels_
parCommune['cluster2'] = cluster2.labels_
parCommune['cluster3'] = cluster3.labels_
parCommune['cluster4'] = cluster4.labels_

parCommuneProp['cluster1'] = cluster1.labels_
parCommuneProp['cluster2'] = cluster2.labels_
parCommuneProp['cluster3'] = cluster3.labels_
parCommuneProp['cluster4'] = cluster4.labels_
```

In [40]:

```
parCommune.head()
```

Out[40]:

| Commune | Nombre_Accident | Blessé hospitalisé | Tué | Conditions_lumière_Crépuscule ou aube | Conditions_lumière_Nuit avec éclairage public allumé | Conditions_lumière_Nuit avec éclairage public non allumé | Conc s |
|---|---|---|---|---|---|---|---|
| **1.0** | 382.0 | 186.0 | 20.0 | 28 | 63 | 3 | |
| **2.0** | 222.0 | 82.0 | 13.0 | 14 | 25 | 2 | |
| **3.0** | 187.0 | 112.0 | 13.0 | 18 | 24 | 0 | |
| **4.0** | 555.0 | 187.0 | 28.0 | 35 | 101 | 5 | |
| **5.0** | 408.0 | 162.0 | 12.0 | 28 | 42 | 7 | |

5 rows × 51 columns

In [ ]:

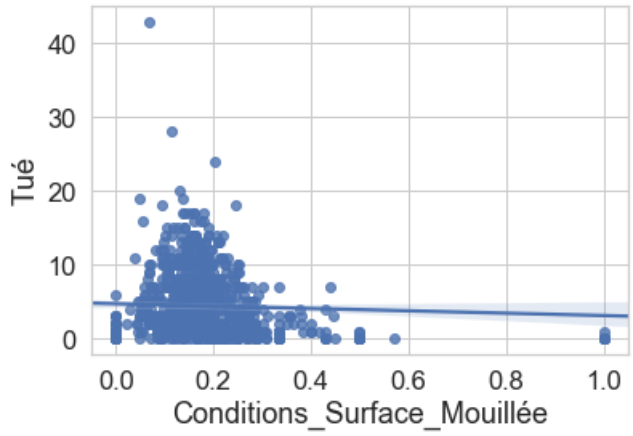
```
```

In [81]:

```
# PLot relationships out
sns.regplot(x='Conditions_Surface_Mouillée',
            y='Tué',
            data=pd.concat((parCommuneProp['Conditions_Surface_Mouillée'],
                            parCommune['Tué']),axis=1))
```

Out[81]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x134f5672b70>
```

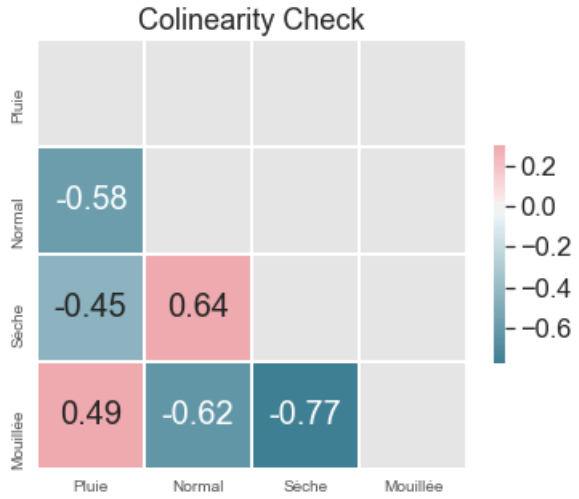



In [ ]:

```
```

In [42]:

```
#%% Colinéarité entre les variables

# Compute the correlation matrix
colin = parCommuneProp[['Atmosphere_Pluie légère',
                        'Atmosphere_Normale',
                        'Conditions_Surface_Normale',
                        'Conditions_Surface_Mouillée']]

labels = np.array(['Pluie',
                   'Normal',
                   'Sèche',
                   'Mouillée'])
corr = colin.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(6, 5))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.set(font_scale=1.5, style='white')
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, annot=True,linewidths=.5, xticklabels=labels,yticklabels=labels,cbar_kws={
"shrink": .5},annot_kws={"size":20})
ax.set_title('Colinearity Check')
plt.savefig('Colinearity Check.png',bbox_inches='tight')
```




## Modèle de regression linéaire pour la plus forte corrélation

In [43]:

```
X = parCommuneProp['Atmosphere_Pluie légère']
y = parCommune['Nombre_Accident']

pCoeff = np.polyfit(X, y, 2)
polynomial = np.poly1d(pCoeff)
```

In [118]:

```
# Calculer la valeur de précision du modèle pour chaque commune
print(np.polyval(pCoeff, X))
```

```
[  71.65988347   77.49261296   82.18936347   77.16271166   84.78280333
   84.02738526   75.50186188   78.41976337   80.69192743   78.35083327
   72.13425173   82.35663089   79.88701886   76.65157333   70.40740878
   67.55688148   87.68378362   82.82653718   80.46345489   71.68805076
   89.82159393   81.60368556   84.10247736   70.57394032   80.73550748
   87.20875014   83.82539317   79.20886278   79.25703258   63.87433857
```

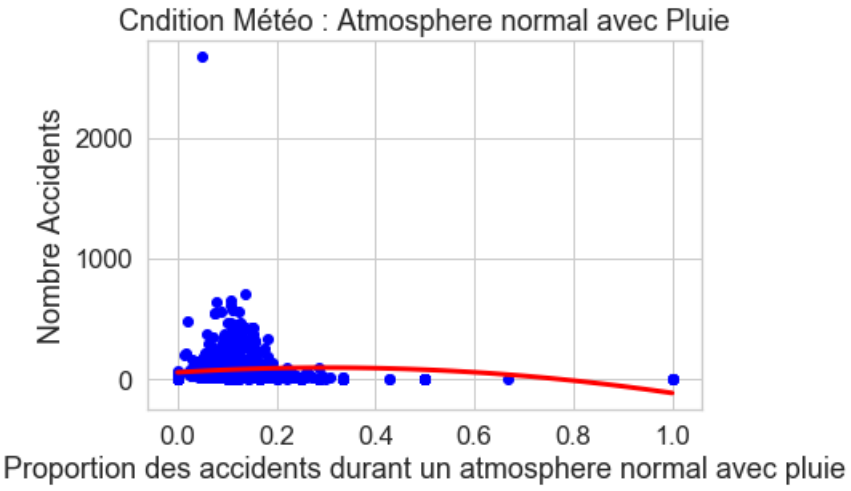
| | | | | |
|---|---|---|---|---|
| 80.95165531 | 71.01772829 | 74.2980123 | 82.97051574 | 81.45029536 |
| 86.28881416 | 89.67030876 | 81.13462417 | 86.82873289 | 77.77898029 |
| 80.56824167 | 83.19267346 | 82.52253599 | 74.77921593 | 81.13462417 |
| 81.91776522 | 84.14644978 | 86.04933312 | 79.05438739 | 82.31755012 |
| 85.8506622 | 82.69732681 | 83.43135057 | 69.18847426 | 69.0497955 |
| 78.41976337 | 84.83037252 | 76.77813422 | 80.08777829 | 83.11727804 |
| 68.76279228 | 78.37241189 | 79.5503255 | 87.68042783 | 78.77100168 |
| 85.22815273 | 89.1575896 | 88.55935627 | 74.55436391 | 83.01113374 |
| 77.58177635 | 86.25084012 | 84.19574304 | 83.89113618 | 82.33323713 |
| 85.16726775 | 84.20632619 | 87.48497358 | 77.50607379 | 77.2008074 |
| 80.70747439 | 83.33191665 | 69.22540021 | 78.02367389 | 90.53380929 |
| 77.85826534 | 75.87480893 | 62.75624378 | 80.63766436 | 79.74085906 |
| 74.82829053 | 64.64500703 | 73.74009001 | 81.39052127 | 72.29704209 |
| 69.27748886 | 74.57029499 | 71.51701597 | 69.95999131 | 80.80116173 |
| 83.71228275 | 81.50174797 | 80.03800475 | 72.98555062 | 77.88455947 |
| 77.76240533 | 78.01027038 | 84.65960923 | 81.09063263 | 86.54398754 |
| 84.51196215 | 80.74724133 | 82.9912225 | 83.45545229 | 87.40977422 |
| 84.95090427 | 80.59596444 | 80.91134893 | 83.81536332 | 86.89853934 |
| 70.57394032 | 87.79352457 | 69.22540021 | 82.56005257 | 77.89480249 |
| 74.76617515 | 81.36183826 | 89.65354659 | 79.17831374 | 82.41058681 |
| 89.51979562 | 70.25963165 | 67.52517649 | 74.57029499 | 57.56840437 |
| 62.13303437 | 70.36271984 | 83.57168725 | 92.95929703 | 77.85826534 |
| 79.97360417 | 75.01727936 | 81.75738704 | 57.56840437 | 65.38784674 |
| 67.8515181 | 83.85049673 | 68.97169691 | 82.26271113 | 63.87433857 |
| 86.86789154 | 76.2410492 | 84.25138472 | 87.87255345 | 78.69198651 |
| 76.2410492 | 75.95499211 | 74.64323931 | 67.8515181 | 80.15968761 |
| 75.24943507 | 78.89057521 | 90.45778664 | 71.61628694 | 81.82842978 |
| 79.76440177 | 83.33191665 | 71.61628694 | 82.63538784 | 90.5888091 |
| 80.73550748 | 72.26247404 | 76.68656816 | 81.75738704 | 87.3640555 |
| 70.05830458 | 68.72871053 | 76.2410492 | 77.6416427 | 79.57735695 |
| 85.62110699 | 87.22751164 | 81.65152664 | 82.48118698 | 75.71154676 |
| 75.01727936 | 83.71228275 | 71.87065734 | 61.28093857 | 66.60660206 |
| 68.49578253 | 83.0375969 | 78.77100168 | 78.02367389 | 77.6416427 |
| 77.6416427 | 86.86789154 | 73.13700563 | 83.89113618 | 83.0375969 |
| 85.00598489 | 72.40756927 | 92.32311375 | 80.63766436 | 69.31247156 |
| 80.91134893 | 74.57029499 | 79.57735695 | 67.65321177 | 81.47694934 |
| 75.01727936 | 80.02647941 | 76.57328333 | 81.75738704 | 84.14644978 |
| 70.467476 | 67.2785613 | 78.98587658 | 80.73550748 | 76.0257106 |
| 63.5144539 | 88.56946157 | 82.18936347 | 76.40575646 | 80.02647941 |
| 79.01142586 | 88.13138692 | 88.13138692 | 72.46344595 | 79.76440177 |
| 76.81763506 | 87.12243167 | 81.82842978 | 75.38267324 | 86.77014337 |
| 74.28448584 | 91.01757225 | 81.47694934 | 86.72840276 | 85.91260374 |
| 79.5503255 | 65.05126959 | 74.79096909 | 80.80116173 | 91.45021802 |
| 70.05830458 | 68.49578253 | 81.65152664 | 85.5441899 | 69.49053686 |
| 81.13462417 | 72.80757382 | 83.73370007 | 74.64323931 | 87.3640555 |
| 84.57045375 | 64.84248676 | 88.92581414 | 88.39323794 | 78.74723862 |
| 87.10587466 | 67.58878774 | 63.5144539 | 70.84784958 | 86.47986556 |
| 76.57328333 | 79.04184023 | 83.33191665 | 96.13273357 | 70.05830458 |
| 89.28724229 | 84.89600725 | 75.98321664 | 82.66779818 | 75.48765522 |
| 85.30286818 | 96.65976833 | 91.51706544 | 81.47694934 | 73.9401334 |
| 82.09822734 | 67.78456079 | 67.46236284 | 82.90576456 | 79.50797276 |
| 81.65152664 | 79.25703258 | 71.19194798 | 80.4762759 | 77.8309444 |
| 88.1915476 | 84.14644978 | 76.2410492 | 84.68808075 | 80.29436987 |
| 68.27230667 | 78.53561352 | 85.91260374 | 76.2410492 | 77.6416427 |
| 66.93060422 | 82.69732681 | 67.8515181 | 78.87722653 | 79.47630829 |
| 65.95334867 | 80.73550748 | 94.05572416 | 80.02647941 | 74.73528014 |
| 79.85112534 | 87.87255345 | 82.86383253 | 77.6416427 | 71.74234903 |
| 87.3640555 | 77.6416427 | 76.2410492 | 90.93148192 | 86.47986556 |
| 82.18936347 | 87.50151742 | 79.25703258 | 64.84248676 | 76.2410492 |
| 87.3640555 | 72.13425173 | 67.2785613 | 71.37067407 | 74.64323931 |
| 88.92581414 | 78.154107 | 73.9401334 | 78.02367389 | 93.37048808 |
| 73.9401334 | 94.33488223 | 87.74427846 | 80.80116173 | 84.31468517 |
| 87.3640555 | 57.56840437 | 68.97169691 | 73.60936006 | 85.00598489 |
| 57.56840437 | 84.31468517 | 78.41976337 | 90.24911689 | 78.77100168 |
| 90.44284164 | 81.82842978 | 68.27230667 | 66.02125116 | 73.44882482 |
| 70.05830458 | 83.33191665 | 81.82842978 | 88.13138692 | 72.13425173 |
| 83.33191665 | 70.68215424 | 91.3713067 | 83.33191665 | 80.34866026 |
| 93.94282985 | 96.74394994 | 72.13425173 | 78.41976337 | 66.60660206 |
| 95.62269919 | 57.56840437 | 88.6580648 | 69.22540021 | 89.57990699 |
| 70.05830458 | 93.88615231 | 77.6416427 | 70.05830458 | 78.41976337 |
| 70.25963165 | 84.71433707 | 81.65152664 | 72.54803982 | 64.64500703 |
| 74.06763145 | 79.60987685 | 73.44882482 | 86.08797685 | 83.93868586 |
| 77.6416427 | 81.13462417 | 57.56840437 | 96.13273357 | 78.45824523 |
| 57.56840437 | 81.13462417 | 57.56840437 | 71.37067407 | 57.56840437 |
| 68.49578253 | 57.56840437 | 71.37067407 | 75.6091107 | 82.18936347 |
| 95.62269919 | 73.24698399 | 83.33191665 | 76.57328333 | 88.13138692 |
| 66.02125116 | 83.93868586 | 74.46200866 | 66.93060422 | 70.87185824 |

```
72.38618771   76.9170724    82.86383253   90.02447258   91.16139914
86.16826047   70.90400337   83.73370007   91.93432008   91.82342914
91.62415651   78.154107     71.37067407   57.56840437   88.28813785
88.28813785   86.62444859   81.13462417   82.41058681   72.98555062
82.18936347   83.33191665   95.03260622   83.33191665   74.73528014
57.56840437   75.01727936   81.82842978   81.13462417   87.60339147
76.2410492    74.35505707   85.36287915   72.98555062   76.2410492
82.18936347   57.56840437   76.2410492    82.26271113   86.86789154
57.56840437   68.05772393   78.41976337   94.05572416   57.56840437
77.6416427    85.6605719    83.15009472   76.9170724    96.65976833
75.01727936   88.92581414   73.9401334    57.56840437   96.33170436
81.13462417   57.56840437   95.62269919   82.7491506    91.16139914
76.2410492    92.00494297   80.15968761   73.9401334    88.28813785
94.60873281   81.59891093   80.91134893   76.2410492    57.56840437
81.13462417   65.50684577   86.47986556   96.72568676   64.84248676
65.05126959   57.56840437   85.91260374   89.74585608   86.47986556
88.92581414   69.49053686   76.46128211   57.56840437   83.81536332
57.56840437   82.7491506    85.91260374   57.56840437   81.13462417
96.40990357   77.6416427    75.01727936   92.32311375   64.84248676
57.56840437   79.64974556   96.75131128   80.15968761   57.56840437
91.62415651   71.37067407   92.32311375   83.33191665   70.05830458
95.99717532   77.6416427    68.97169691   88.92581414   76.2410492
73.9401334    84.38734177   67.2785613    65.75600789   57.56840437
57.56840437   75.01727936   57.56840437   68.49578253   92.32311375
57.56840437   57.56840437   77.6416427    86.86789154   80.00441988
57.56840437   57.56840437   71.37067407   62.32056549   64.94540569
92.32311375   75.01727936   85.91260374   83.93868586   72.33829974
80.15968761   57.56840437   82.18936347   81.13462417   74.60758081
57.56840437   72.98555062   79.25703258   96.65976833   72.13425173
57.56840437   73.9401334    72.98555062   76.2410492    90.24911689
92.32311375   96.33170436   57.56840437   57.56840437   67.65321177
90.24911689   85.45329446   96.33170436   95.03260622   57.56840437
57.56840437   83.33191665   64.84248676   57.56840437   91.16139914
81.13462417   93.95614411   57.56840437   81.13462417   87.58047854
71.37067407   72.98555062   57.56840437   90.98444176   57.56840437
93.48581538   57.56840437   88.92581414   96.65976833   96.65976833
96.33170436   95.62269919   88.92581414   68.27230667   88.92581414
87.3640555    75.81511346   70.68215424   57.56840437   77.6416427
75.73216908   67.65321177   57.56840437   57.56840437   57.56840437
65.00856262   57.56840437   79.25703258   95.62269919   57.56840437
57.56840437   85.91260374   57.56840437   57.56840437   57.56840437
57.56840437   57.56840437   81.13462417   75.01727936   57.56840437
57.56840437   79.78607504   57.56840437   96.76664788   94.87600141
68.97169691   95.62269919   57.56840437   95.62269919   96.33170436
57.56840437   57.56840437   57.56840437   57.56840437   84.57045375
76.2410492    95.62269919   57.56840437   96.65976833   96.05475544
76.2410492    82.18936347   88.92581414   57.56840437   84.57045375
57.56840437   57.56840437   75.01727936   57.56840437   57.56840437
82.56005257   57.56840437   90.5888091    57.56840437   73.9401334
57.56840437   85.91260374   57.56840437   94.60873281   79.25703258
57.56840437   88.92581414   57.56840437   57.56840437   95.62269919
91.45021802   57.56840437   89.80989816   95.62269919   96.33170436
73.9401334    96.40990357   77.6416427    76.9170724    81.13462417
89.80989816   79.25703258   57.56840437   95.62269919   95.13523304
88.92581414   94.53110251   57.56840437   75.01727936   64.4579393
96.33170436   57.56840437   96.33170436   57.56840437   57.56840437
57.56840437   90.5888091    95.62269919   57.56840437   57.56840437
57.56840437   96.33170436   57.56840437   79.78607504   57.56840437
83.33191665   83.33191665   57.56840437   57.56840437   79.25703258
57.56840437   79.78607504   79.78607504   79.78607504   77.6416427
79.78607504   87.3640555    96.65976833   57.56840437   79.78607504
57.56840437   57.56840437   57.56840437   79.78607504   57.56840437
95.62269919   57.56840437   57.56840437   57.56840437   57.56840437
39.28892619   57.56840437   57.56840437   57.56840437   79.78607504
81.13462417   57.56840437   57.56840437   57.56840437   81.13462417
96.33170436   57.56840437   57.56840437   96.65976833   57.56840437
57.56840437   57.56840437 -113.55993015   57.56840437   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437 -113.55993015
57.56840437   57.56840437   57.56840437 -113.55993015   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
57.56840437   57.56840437   57.56840437   79.78607504   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437   88.92581414
57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
57.56840437   57.56840437   57.56840437   57.56840437 -113.55993015
57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
```

```
   57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
   57.56840437   57.56840437   57.56840437   57.56840437   57.56840437
   57.56840437]
```

In [44]:

```
sns.set_style("whitegrid", {'axes.grid' : True})
# Plot Model Results
xp = np.linspace(X.min(), X.max(), 100)
fig5 = plt.figure()
axes = fig5.add_axes([0.1, 0.1, 0.8, 0.8])
axes.scatter(X,y,c='blue')
axes.plot(xp, polynomial(xp), linewidth = 3, c='red')
axes.set_title('Cndition Météo : Atmosphere normal avec Pluie')
axes.set_xlabel('Proportion des accidents durant un atmosphere normal avec pluie')
axes.set_ylabel('Nombre Accidents')
plt.savefig('Raining, no high winds vs Accident.png')
```




In [45]:

```
#Add cluster labels to byLA and byLAnorm tables
parCommune['cluster4'] = cluster4.labels_
parCommuneProp['cluster4'] = cluster4.labels_
parCommune['cluster4'] = parCommune['cluster4'].astype('str')
parCommuneProp['cluster4'] = parCommuneProp['cluster4'].astype('str')
```

In [46]:

```
parCommune.head()
```

Out[46]:

| Commune | Nombre_Accident | Blessé hospitalisé | Tué | Conditions_lumière_Crépuscule ou aube | Conditions_lumière_Nuit avec éclairage public allumé | Conditions_lumière_Nuit avec éclairage public non allumé | Conc s |
|---|---|---|---|---|---|---|---|
| **1.0** | 382.0 | 186.0 | 20.0 | 28 | 63 | 3 | |
| **2.0** | 222.0 | 82.0 | 13.0 | 14 | 25 | 2 | |
| **3.0** | 187.0 | 112.0 | 13.0 | 18 | 24 | 0 | |
| **4.0** | 555.0 | 187.0 | 28.0 | 35 | 101 | 5 | |
| **5.0** | 408.0 | 162.0 | 12.0 | 28 | 42 | 7 | |

5 rows × 51 columns

## Déterminer les profiles des clusters des communes

In [47]:

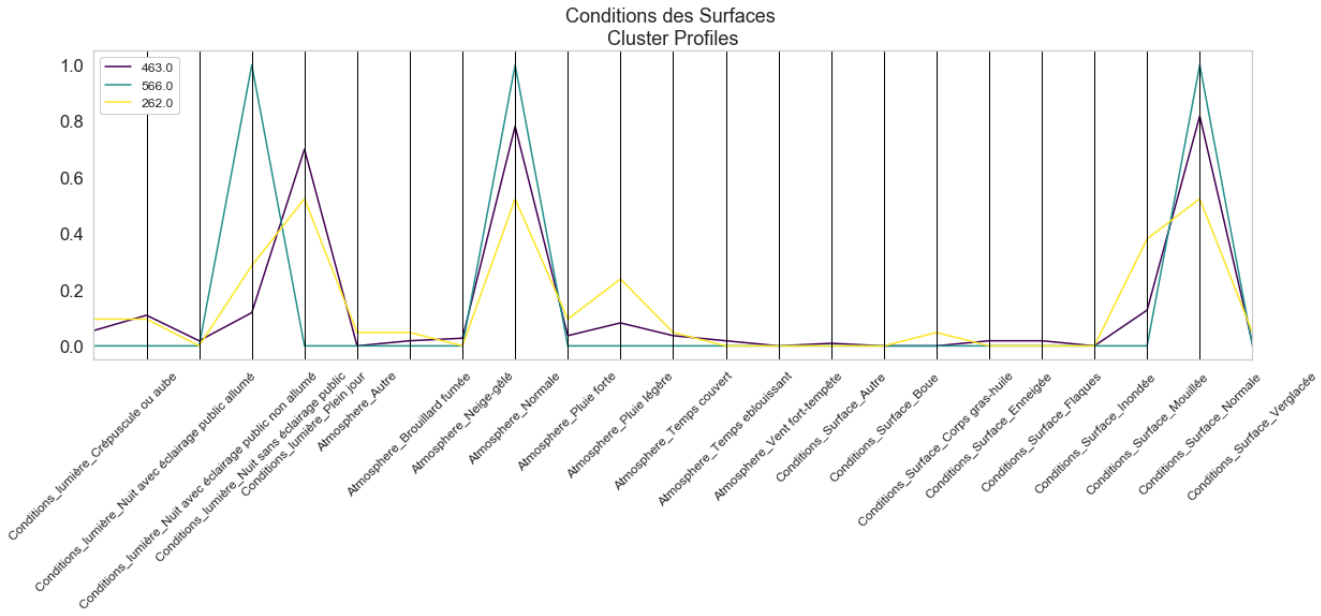
```
#Déterminer les profiles des communes les plus proches au centres des cluster
```

```
#Determiner les profiles des communes les plus proches au centres des cluster:

from sklearn.metrics import pairwise_distances_argmin_min

closest1, _ = pairwise_distances_argmin_min(cluster1.cluster_centers_, parCommuneProp[toutesCols])
closest2, _ = pairwise_distances_argmin_min(cluster2.cluster_centers_, parCommuneProp[lumCols])
closest3, _ = pairwise_distances_argmin_min(cluster3.cluster_centers_, parCommuneProp[atmCols])
closest4, _ = pairwise_distances_argmin_min(cluster4.cluster_centers_, parCommuneProp[surfCols])

closest1 = parCommuneProp.iloc[closest1]
closest2 = parCommuneProp.iloc[closest2]
closest3 = parCommuneProp.iloc[closest3]
closest4 = parCommuneProp.iloc[closest4]
```

In [79]:

```
import sys
import pandas
from pandas.tools.plotting import parallel_coordinates

#Plot Parallel Coordinates PLot
fig = plt.figure()
axes = fig.add_axes([0.5, 0.5, 2.5, 1])
parallel_coordinates(pd.concat((closest1[toutesCols],closest1['cluster1']), axis=1), 'cluster1',co
lormap='viridis')
plt.title('Conditions des Surfaces \nCluster Profiles')
plt.legend(labels=closest4.index,frameon=True,framealpha=1,fontsize=12)

for tick in axes.get_xticklabels():
    tick.set_rotation(45)
    tick.set_fontsize(12)

plt.savefig('Surface PCP ',bbox_inches='tight')
```

```
c:\users\jileni\anaconda3\envs\ml\lib\site-packages\ipykernel_launcher.py:8: FutureWarning:
'pandas.tools.plotting.parallel_coordinates' is deprecated, import
'pandas.plotting.parallel_coordinates' instead.
```

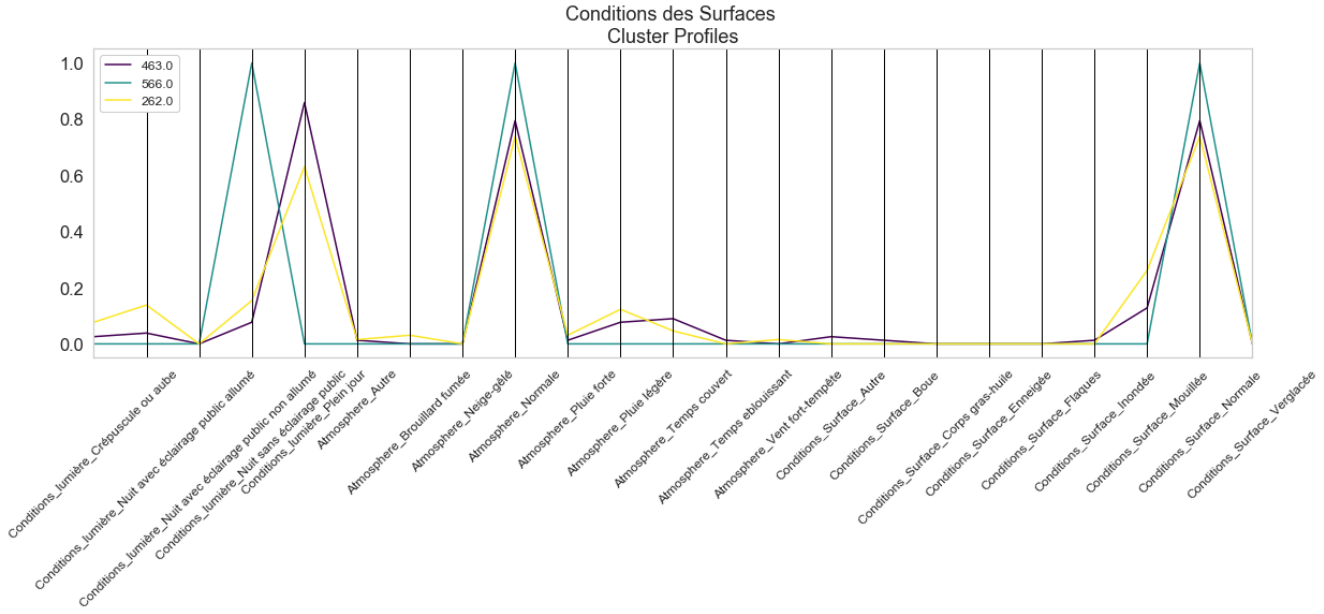



In [77]:

```
fig = plt.figure()
axes = fig.add_axes([0.5, 0.5, 2.5, 1])
parallel_coordinates(pd.concat((closest2[toutesCols],closest2['cluster2']), axis=1), 'cluster2',co
lormap='viridis')
plt.title('Conditions des Surfaces \nCluster Profiles')
plt.legend(labels=closest4.index,frameon=True,framealpha=1,fontsize=12)

for tick in axes.get_xticklabels():
    tick.set_rotation(45)
    tick.set_fontsize(12)
```

```
plt.savefig('Surface PCP 2',bbox_inches='tight')
```

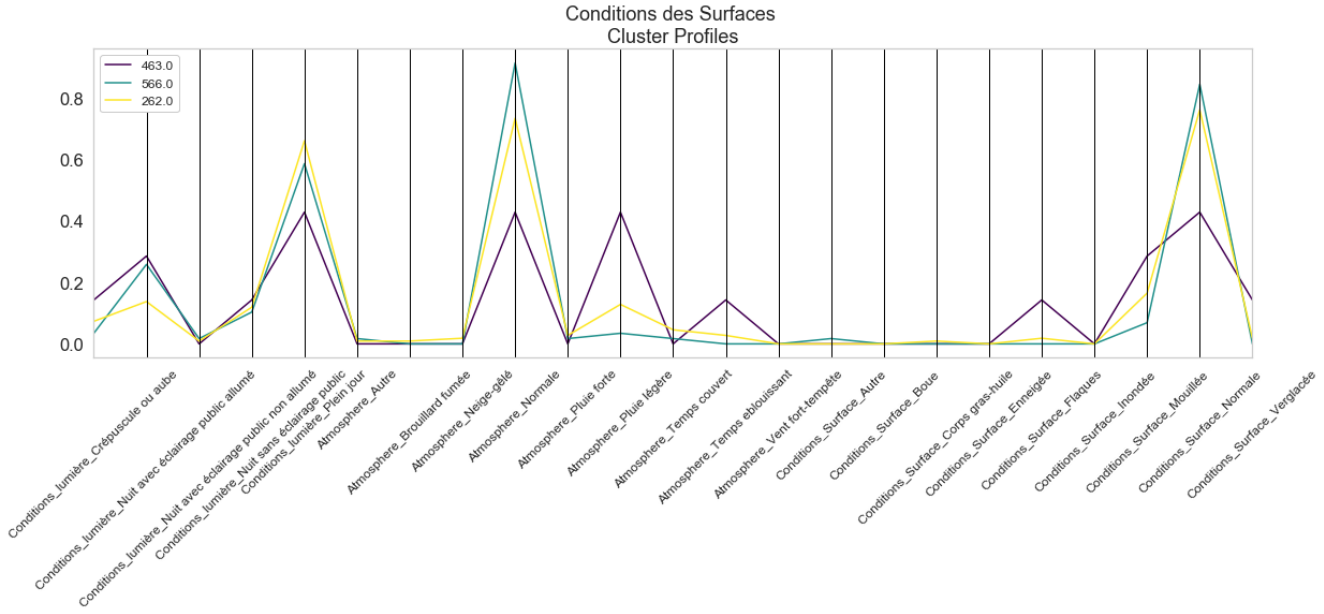
```
c:\users\jileni\anaconda3\envs\ml\lib\site-packages\ipykernel_launcher.py:3: FutureWarning:
'pandas.tools.plotting.parallel_coordinates' is deprecated, import
'pandas.plotting.parallel_coordinates' instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```




In [76]:

```
fig = plt.figure()
axes = fig.add_axes([0.5, 0.5, 2.5, 1])
parallel_coordinates(pd.concat((closest3[toutesCols],closest3['cluster3']), axis=1), 'cluster3',co
lormap='viridis')
plt.title('Conditions des Surfaces \nCluster Profiles')
plt.legend(labels=closest4.index,frameon=True,framealpha=1,fontsize=12)

for tick in axes.get_xticklabels():
    tick.set_rotation(45)
    tick.set_fontsize(12)

plt.savefig('Surface PCP 3 ',bbox_inches='tight')
```

```
c:\users\jileni\anaconda3\envs\ml\lib\site-packages\ipykernel_launcher.py:3: FutureWarning:
'pandas.tools.plotting.parallel_coordinates' is deprecated, import
'pandas.plotting.parallel_coordinates' instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```



In [73]:

```
fig = plt.figure()
axes = fig.add_axes([0.5, 0.5, 2.5, 1])
parallel_coordinates(pd.concat((closest4[toutesCols],closest4['cluster4']), axis=1), 'cluster4',co
lormap='viridis')
plt.title('Conditions des Surfaces \nCluster Profiles')
plt.legend(labels=closest4.index,frameon=True,framealpha=1,fontsize=12)

for tick in axes.get_xticklabels():
    tick.set_rotation(45)
    tick.set_fontsize(12)

plt.savefig('Surface PCP 4',bbox_inches='tight')
```

```
c:\users\jileni\anaconda3\envs\ml\lib\site-packages\ipykernel_launcher.py:3: FutureWarning:
'pandas.tools.plotting.parallel_coordinates' is deprecated, import
'pandas.plotting.parallel_coordinates' instead.
  This is separate from the ipykernel package so we can avoid doing imports until
```