Importer les packages

In [23]:
```python
import pyforest
import lazypredict
from lazypredict.Supervised import LazyClassifier
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
# Hide warnings
import warnings
warnings.filterwarnings('ignore')
```

Importer les données

In [37]:
```python
Urbanisation_data = pd.read_csv('Urbanization_Data_MML.csv')
```

In [38]:
```python
Urbanisation_data= Urbanisation_data.drop(['Unnamed: 0'], axis = 1)
```

In [39]:
```python
Urbanisation_data.tail()
```

Out[39]:

	region	Date	Effectif de la population	Population rurale	Population urbaine	Taux d'urbanisation	Nombre de ménages ruraux	Nombre de ménages urbains	moy mén
507	Ziguinchor	2014	565940.00	303344.00	262596.00	46.40	50814.08	40063.58	
508	Ziguinchor	2015	583528.00	309854.00	273674.00	46.90	50814.08	40063.58	
509	Ziguinchor	2016	601929.00	317216.00	284713.00	47.30	50814.08	40063.58	
510	Ziguinchor	2017	621168.00	324250.00	296918.00	47.80	50814.08	40063.58	
511	Ziguinchor	2018	641254.00	332170.00	309084.00	48.20	50814.08	40063.58	

Exploration des données

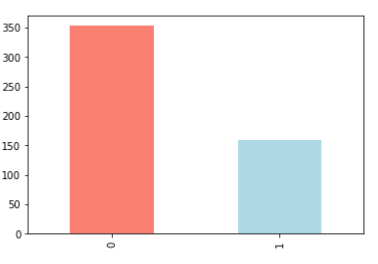
In [5]:
```python
pd.set_option("display.float", "{:.2f}".format)
Urbanisation_data.describe()
```

Out[5]:

	Date	Effectif de la population	Population rurale	Population urbaine	Taux d'urbanisation	Nombre de ménages ruraux	Nombre de ménages urbains	Taill moyenn des ménage
count	512.00	512.00	512.00	512.00	512.00	512.00	512.00	512.0
mean	1994.80	786769.36	463799.61	322712.98	30.05	50814.08	40063.58	7.9
std	14.41	521011.50	234370.01	550205.13	23.56	17966.71	55553.61	0.1
min	1970.00	122333.00	27614.74	20054.00	7.51	2785.35	3867.33	7.4
25%	1982.00	480522.11	338683.24	82088.50	15.54	49939.38	12643.48	7.9
50%	1995.00	642156.40	456375.94	137861.49	21.83	50814.08	25930.51	7.9
75%	2007.00	885796.16	573673.31	259445.00	35.69	56703.03	40063.58	7.9
max	2018.00	3630324.00	1463564.00	3499631.00	97.22	100729.97	321110.09	9.2

In [6]:
```python
Urbanisation_data.risque_déforestation.value_counts().plot(kind="bar", color=["salmon", "lightblue"])
```

Out[6]: <AxesSubplot:>



In [7]:
```python
Urbanisation_data.isna().sum()
```

Out[7]:
```
region                             0
Date                               0
Effectif de la population          0
Population rurale                  0
Population urbaine                 0
Taux d'urbanisation                0
Nombre de ménages ruraux           0
Nombre de ménages urbains          0
Taille moyenne des ménages         0
Taille moyenne des ménages ruraux  0
Taille moyenne des ménages urbains 0
risque_déforestation               0
dtype: int64
```

Sélection des variables continues

In [8]:
```python
Urbanisation_data = Urbanisation_data.drop(['region', 'Date'], axis= 1 )
Urbanisation_data.head()
```

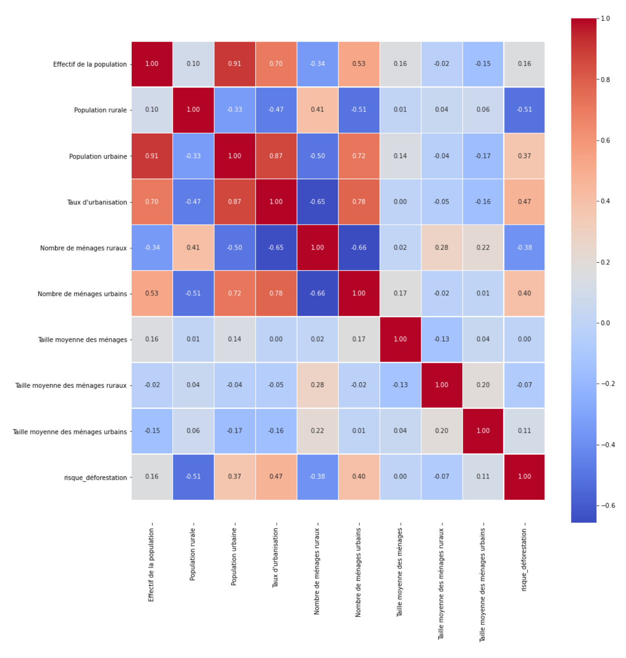
Out[8]:

	Effectif de la population	Population rurale	Population urbaine	Taux d'urbanisation	Nombre de ménages ruraux	Nombre de ménages urbains	Taille moyenne des ménages	Taille moyenne des ménages ruraux	m m
0	724461.69	27614.74	696846.95	96.19	2785.35	97871.76	7.55	9.91	
1	759203.25	28805.87	730397.38	96.21	2928.70	101632.29	7.52	9.84	
2	795610.84	30048.38	765562.46	96.22	3079.63	105546.30	7.48	9.76	
3	833764.36	31344.49	802419.87	96.24	3238.55	109620.20	7.45	9.68	
4	873747.53	32696.50	841051.03	96.26	3405.89	114397.58	7.42	9.60	

Matrice de corrélation

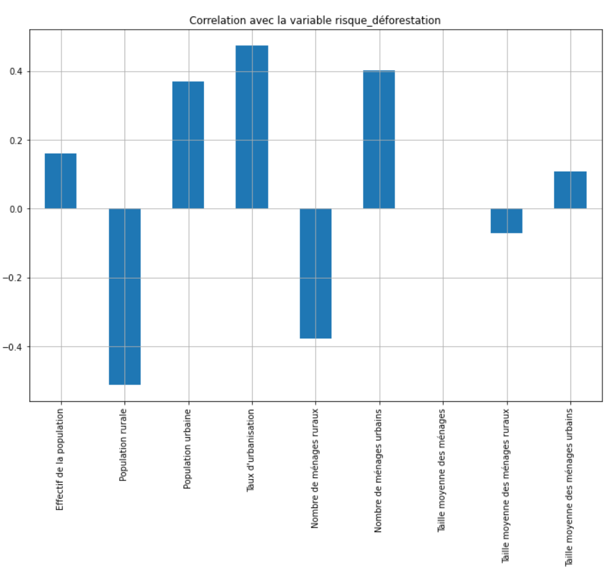
In [9]:
```python
# Let's make our correlation matrix a little prettier
corr_matrix = Urbanisation_data.corr()
fig, ax = plt.subplots(figsize=(15, 15))
ax = sns.heatmap(corr_matrix,
                 annot=True,
                 linewidths=0.5,
                 fmt=".2f",
                 cmap="coolwarm");
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
```

Out[9]: (10.5, -0.5)



In [10]:
```python
Urbanisation_data.drop('risque_déforestation', axis=1).corrwith(Urbanisation_data.risque_déforestation).plot(kind='bar', grid=True, figsize=(12, 8),
                                                                   title="Correlation avec la variable risque_déforestation")
```

Out[10]: <AxesSubplot:title={'center':'Correlation avec la variable risque_déforestation'}>



Commentaires

- On voit les variables 'Population rurale', 'Population urbaine', 'Taux d'urbanisation' et 'Nombre de ménages urbains' sont plus correlées avec la variable 'risque_déforestation' contrairement aux autres.
- Donc les variables citées ci-dessus sont considérées comme de bons prédicteurs.

Sélection des variables les plus corrélées avec la variable cible

In [11]:
```python
Selected_columns = ['Population rurale', 'Population urbaine',
       "Taux d'urbanisation", 'Nombre de ménages urbains', 'risque_déforestation']
```

In [12]:
```python
Urbanisation_data = Urbanisation_data[Selected_columns]
```

Transformation des données

In [13]:
```python
X = Urbanisation_data.drop(['risque_déforestation'], axis  = 1 )
y = Urbanisation_data.risque_déforestation
```

In [14]:
```python
from sklearn.preprocessing import StandardScaler
s_sc = StandardScaler()
X = s_sc.fit_transform(X)
```

Fractionner les données

In [15]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)
```

Appliquer du modèle RandomForest

In [16]:
```python
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

def print_score(clf, X_train, y_train, X_test, y_test, train=True):
    if train:
        pred = clf.predict(X_train)
        clf_report = pd.DataFrame(classification_report(y_train, pred, output_dict=True))
        print("Train Result:\n================================================")
        print(f"Accuracy Score: {accuracy_score(y_train, pred) * 100:.2f}%")
        print("_______________________________________________")
        print(f"CLASSIFICATION REPORT:\n{clf_report}")
        print("_______________________________________________")
        print(f"Confusion Matrix: \n {confusion_matrix(y_train, pred)}\n")

    elif train==False:
        pred = clf.predict(X_test)
        clf_report = pd.DataFrame(classification_report(y_test, pred, output_dict=True))
        print("Test Result:\n================================================")
        print(f"Accuracy Score: {accuracy_score(y_test, pred) * 100:.2f}%")
        print("_______________________________________________")
        print(f"CLASSIFICATION REPORT:\n{clf_report}")
        print("_______________________________________________")
        print(f"Confusion Matrix: \n {confusion_matrix(y_test, pred)}\n")
```

Trouver les paramètres optimaux du modèle

In [25]:
```python
rfc =RandomForestClassifier(random_state=42)
```

In [26]:
```python
param_grid = {
    'n_estimators': [200, 500],
    'max_features': ['auto', 'sqrt', 'log2'],
    'max_depth' : [4,5,6,7,8],
    'criterion' :['gini', 'entropy']
}
```

In [27]:
```python
CV_rfc = GridSearchCV(estimator=rfc, param_grid=param_grid, cv= 5)
CV_rfc.fit(X_train, y_train)
```

Out[27]:
```
GridSearchCV(cv=5, error_score=nan,
             estimator=RandomForestClassifier(bootstrap=True, ccp_alpha=0.0,
                                              class_weight=None,
                                              criterion='gini', max_depth=None,
                                              max_features='auto',
                                              max_leaf_nodes=None,
                                              max_samples=None,
                                              min_impurity_decrease=0.0,
                                              min_impurity_split=None,
                                              min_samples_leaf=1,
                                              min_samples_split=2,
                                              min_weight_fraction_leaf=0.0,
                                              n_estimators=100, n_jobs=None,
                                              oob_score=False, random_state=42,
                                              verbose=0, warm_start=False),
             iid='deprecated', n_jobs=None,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [4, 5, 6, 7, 8],
                         'max_features': ['auto', 'sqrt', 'log2'],
                         'n_estimators': [200, 500]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=False,
             scoring=None, verbose=0)
```

In [28]:
```python
CV_rfc.best_params_
```

Out[28]:
```
{'criterion': 'entropy',
 'max_depth': 8,
 'max_features': 'auto',
 'n_estimators': 500}
```

Application du modèle avec les paramètres optimaux obtenus

In [32]:
```python
rfc1=RandomForestClassifier(random_state=42, max_features='auto', n_estimators= 500,
                            max_depth=8, criterion='entropy')
rfc1.fit(X_train, y_train)
```

Out[32]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='entropy', max_depth=8, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=500,
                       n_jobs=None, oob_score=False, random_state=42, verbose=0,
                       warm_start=False)
```

In [34]:
```python
print_score(rfc1, X_train, y_train, X_test, y_test, train=True)
print_score(rfc1, X_train, y_train, X_test, y_test, train=False)
```

```
Train Result:
================================================
Accuracy Score: 98.60%
_______________________________________________
CLASSIFICATION REPORT:
               0      1  accuracy  macro avg  weighted avg
precision   0.98   1.00      0.99       0.99          0.99
recall      1.00   0.95      0.99       0.98          0.99
f1-score    0.99   0.98      0.99       0.98          0.99
support   247.00 111.00      0.99     358.00        358.00
_______________________________________________
Confusion Matrix:
 [[247   0]
 [  5 106]]


Test Result:
================================================
Accuracy Score: 92.21%
_______________________________________________
CLASSIFICATION REPORT:
               0     1  accuracy  macro avg  weighted avg
precision   0.90  1.00      0.92       0.95          0.93
recall      1.00  0.75      0.92       0.88          0.92
f1-score    0.95  0.86      0.92       0.90          0.92
support   106.00 48.00      0.92     154.00        154.00
_______________________________________________
Confusion Matrix:
 [[106   0]
 [ 12  36]]
```

Prédiction

In [35]:
```python
def Prédiction(Value):
    if Value == [1]:
        print('PREDICTION : \n La région est fortement menacée par la déforestation')
    else:
        print('PREDICTION : \n La région est faiblement menacée par la déforestation')
```

In [36]:
```python
Value = rfc1.predict([[468595.24, 64072.71, 12.03, 9206.00]])
Prédiction(Value)
```

```
PREDICTION :
 La région est faiblement menacée par la déforestation
```

In [ ]: