

Robust Successive Binarizations (RSB) for Change Detection in Hyperspectral Images

In [1]:

```
1 #Necessary Libraries to be imported:  
2 import numpy as np  
3 import matplotlib.pyplot as plt  
4 import matplotlib.image as mpimg  
5 import time  
6 from os.path import dirname, join as pjoin  
7 from scipy.io import loadmat  
8 from sklearn.metrics import confusion_matrix  
9 import cv2  
10 from sklearn.naive_bayes import GaussianNB  
11 from scipy import stats
```

LOAD the DATASETS

Please, replace the following `filepath` , `filepathU` , `filepathR` string with your own.

In [2]:

```
1 filepath = 'C:/Users/antonella/Downloads/ChangeDetectionDataset-master-Hermiston/Change  
2 her1 = pjoin(filepath, 'hermiston2004.mat')  
3 her2 = pjoin(filepath, 'hermiston2007.mat')  
4 gt = pjoin(filepath, 'rdChangesHermiston_5classes.mat')
```

In [3]:

```
1 filepathU = 'C:/Users/antonella/Downloads/Hyperspectral_Change_Datasets'  
2 usa1 = pjoin(filepathU, 'USA1.mat')  
3 usa2 = pjoin(filepathU, 'USA2.mat')  
4 gtU = pjoin(filepathU, 'USA_gt.mat')
```

In [4]:

```
1 filepathR = 'C:/Users/antonella/Downloads/GETNET/zuixin'  
2 river1 = pjoin(filepathR, 'river_before.mat')  
3 river2 = pjoin(filepathR, 'river_after.mat')  
4 gtR = pjoin(filepathR, 'groundtruth.mat')
```

In [5]:

```
1 her1 = loadmat(her1) # Dictionary
2 her1 = her1['HypeRview']
3 her1 = her1.astype(float)
4 her2 = loadmat(her2) # Dictionary
5 her2 = her2['HypeRview']
6 her2 = her2.astype(float)
7
8 usa1 = loadmat(usa1)
9 usa1 = usa1['USA1']
10 usa1 = usa1.astype(float)
11 usa2 = loadmat(usa2) # Dictionary
12 usa2 = usa2['USA2']
13 usa2 = usa2.astype(float)
14
15 river1 = loadmat(river1)
16 river1 = river1['river_before']
17 river1 = river1.astype(float)
18 river2 = loadmat(river2) # Dictionary
19 river2 = river2['river_after']
20 river2 = river2.astype(float)
```

In [6]:

```
1 gt = loadmat(gt)
2 gt = gt['gt5clasesHermiston']
3 gt = gt.astype(float)
4
5 gtU = loadmat(gtU)
6 gtU = gtU['USA_gt']
7 gtU = gtU.astype(float)
8
9 gtR = loadmat(gtR)
10 gtR = gtR['lakelabel_v1']
11 gtR = gtR.astype(float)
```

In [7]:

```
1 # Hermiston GT is given for multi-class, hence in order to produce only the binary map
2 # changed/not-changed pixels, we need to set to 1 all the changed pixels
3
4 n2 = np.where(gt.ravel() == 2)
5 n3 = np.where(gt.ravel() == 3)
6 n4 = np.where(gt.ravel() == 4)
7 n5 = np.where(gt.ravel() == 5)
8
9 new_gt = gt.ravel()
10 ##### &&& Only for Hermiston
11 new_gt[n2] = 1
12 new_gt[n3] = 1
13 new_gt[n4] = 1
14 new_gt[n5] = 1
```

In [8]:

```
1 [m1,n1,k1] = her1.shape
2 print('Hermiston dataset size ', m1,n1,k1)
3
4 H1 = np.reshape(her1,[m1*n1,k1])
5 print('Hermiston vectorized ', H1.shape)
6
7 [m2,n2,k2] = her2.shape
8
9 H2 = np.reshape(her2,[m2*n2,k2])
10
11 [mu1,nu1,ku1] = usa1.shape
12 print('USA dataset size ', mu1,nu1,ku1)
13
14 U1 = np.reshape(usa1,[mu1*nu1,ku1])
15 print('USA vectorized ', U1.shape)
16
17 [mu2,nu2,ku2] = usa2.shape
18
19 U2 = np.reshape(usa2,[mu2*nu2,ku2])
20
21 [mr1, nr1, kr1] = river1.shape
22 print('River dataset size ', mr1, nr1, kr1)
23
24 R1 = np.reshape(river1,[mr1*nr1,kr1])
25 print('River vectorized ', R1.shape)
26
27 [mr2, nr2, kr2] = river2.shape
28
29 R2 = np.reshape(river2,[mr2*nr2,kr2])
```

```
Hermiston dataset size 390 200 242
Hermiston vectorized (78000, 242)
USA dataset size 307 241 154
USA vectorized (73987, 154)
River dataset size 463 241 198
River vectorized (111583, 198)
```

Error Function Definitions

In [9]:

```
1 def SAM(x,y):
2     norm2_x = np.linalg.norm(x)
3     norm2_y = np.linalg.norm(y)
4     return np.arccos(np.dot(x,y)/(norm2_x*norm2_y))
5
6
7 def SAM_MEAN(A, B, windowSize=2):
8     row, col, feature= A.shape
9     C= np.zeros([row, col])
10    windSizeMatrix=np.zeros((row, col))
11
12    for i in range(-windowSize, +windowSize+1):
13        for j in range(-windowSize, +windowSize+1):
14            rowS=max(0,i)
15            rowE=min(row, row+i)
16            colS=max(0,j)
17            colE=min(col, col+j)
18            windSizeMatrix[row-rowE:row-rowS, col-colE:col-colS]+=1
19            den1= np.sqrt(np.sum(np.multiply(A[rowS:rowE, colS:colE], A[rowS:rowE, colS:colE])))
20            den1[den1 < 1e-5]=1e-5
21
22            den2= np.sqrt(np.sum(np.multiply(B[rowS:rowE, colS:colE], B[rowS:rowE, colS:colE])))
23            den2[den2 < 1e-5]=1e-5
24            num=np.sum(np.multiply(A[rowS:rowE, colS:colE],B[rowS:rowE, colS:colE]),axis=2)
25            ndiv = np.divide(num, np.multiply(den1,den2))
26            ndiv[ndiv > 1] = 1.
27            ndiv[ndiv <-1] = -1.
28            count=np.arccos(ndiv)
29
30            C[row-rowE:row-rowS, col-colE:col-colS]+=count
31
32
33    C=np.divide(C, windSizeMatrix).reshape(row,col)
34
35    return C
```

In [10]:

```
1 def newSSCC(A, B, windowSize=2):
2
3     row, col, feature = A.shape
4
5     nPixel = row * col
6     sumA = A.sum(axis=2)
7     sumB = B.sum(axis=2)
8
9     BwindowMean = np.zeros(sumB.shape)
10    numT = np.zeros(sumA.shape)
11    den2T = np.zeros(sumA.shape)
12    denT = np.zeros(sumA.shape)
13
14    AwindowMean = np.zeros(sumA.shape)
15    windSizeMatrix = np.zeros(sumA.shape)
16    den1T = np.zeros(sumA.shape)
17
18    for i in range(-windowSize, +windowSize+1):
19        for j in range(-windowSize, +windowSize+1):
20            rowS = max(0, i)
21            rowE = min(row, row+i)
22            colS = max(0, j)
23            colE = min(col, col+j)
24            AwindowMean[row - rowE:row - rowS, col - colE:col - colS] += sumA[rowS:rowE, colS:colE]
25
26            BwindowMean[row - rowE:row - rowS, col - colE:col - colS] += sumB[rowS:rowE, colS:colE]
27            windSizeMatrix[row - rowE:row - rowS, col - colE:col - colS] += 1
28 #windSizeMatrix = np.multiply(windSizeMatrix, windSizeMatrix)
29    AwindowMean = AwindowMean / (feature)
30    #print('\n max AwindowMean ', np.max(AwindowMean))
31    BwindowMean = BwindowMean / (feature)
32    #print('\n max BwindowMean ', np.max(BwindowMean))
33    #print('\n max windSizeMatrix ', np.max(windSizeMatrix))
34    BwindowMean = np.divide(BwindowMean, windSizeMatrix)
35    AwindowMean = np.divide(AwindowMean, windSizeMatrix)
36    #print('\n First division ')
37
38    for i in range(-windowSize, +windowSize+1):
39        for j in range(-windowSize, +windowSize+1):
40            rowS = max(0, i)
41            rowE = min(row, row+i)
42            colS = max(0, j)
43            colE = min(col, col+j)
44            Asubtract = np.zeros(A.shape)
45            Bsubtract = np.zeros(A.shape)
46
47
48            Asubtract[rowS:rowE, colS:colE] = A[rowS:rowE, colS:colE] - AwindowMean[rowS:rowE, colS:colE]
49            Bsubtract[rowS:rowE, colS:colE] = B[rowS:rowE, colS:colE] - BwindowMean[rowS:rowE, colS:colE]
50
51            den1T[row - rowE:row - rowS, col - colE:col - colS] += np.einsum('ijn,ijn->ij', Asubtract, Bsubtract)
52
53            numT[row - rowE:row - rowS, col - colE:col - colS] += np.einsum('ijn,ijn->ij', Asubtract, Asubtract)
54            den2T[row - rowE:row - rowS, col - colE:col - colS] += np.einsum('ijn,ijn->ij', Bsubtract, Bsubtract)
55
56            denT = np.multiply(np.sqrt(den1T), np.sqrt(den2T))
57            denT[denT < 1e-5] = 1e-5
58            #print('\n max den1T ', np.max(den1T))
59            #print('\n max den2T ', np.max(den2T))
```

```
60     C=1-np.divide(numT,denT).reshape(row, col)
61     #print('\n second division ')
62     return C
63
```

In [11]:

```
1 def nor01(matrix):
2     mi=(matrix.min())
3     ma=(matrix).max()
4     return (matrix-mi)/(ma-mi)
5
6 def Scale(Matrix):
7     minMat = np.min(Matrix)
8     MaxMat = np.max(Matrix)
9     return 1/(MaxMat-minMat+1e-8)*(Matrix-minMat)
10
11 def SAM_ZID(A,B):
12     row, column, feature= A.shape
13     nPixel=row*column
14     sam = np.zeros([1,nPixel])
15     Ac = A.reshape(nPixel,feature)
16     Bc = B.reshape(nPixel,feature)
17     for i in range(nPixel):
18         sam[0,i] = SAM(Ac[i,:], Bc[i,:])
19     diffe = abs(Ac-Bc)
20     temp = np.zeros([nPixel, feature])
21     for k in range(nPixel):
22         temp[k,:] = ((diffe[k,:]-np.mean(diffe[k,:]))/np.std(diffe[k,:]))**2
23     zid = np.sum(temp, axis=1)
24     sin_angle = nor01( np.sin( sam ) )
25     zidj = nor01(zid)
26     sam_zid= np.prod([[sin_angle[0,:],zidj]], axis=1)
27
28     return sam_zid
29
30 def ZID_g_mod(A,B):
31     row, column, feature= A.shape
32     nPixel=row*column
33     A= (A.reshape(nPixel,feature))
34     B = B.reshape(nPixel,feature)
35     mu_g0=np.zeros([nPixel,1] )
36     sigma_g0 = np.zeros([nPixel,1] )
37     muB=np.zeros([nPixel,1] )
38     sigmaB = np.zeros([nPixel,1] )
39     muA=np.zeros([nPixel,1] )
40     sigmaA = np.zeros([nPixel,1] )
41     C0 =np.copy(abs(A-B)) # modified
42
43     eta = 1e-10
44     mu_g0[:,0] = ( (np.sum(np.log(( C0+eta)),axis=1)/A.shape[1]) )
45
46     sigma_g0[:,0] = ( np.sum((( C0+eta-mu_g0)**2), axis=1)/(A.shape[1]) )
47     sigma_g0[sigma_g0 < 1e-10]=1e-5
48
49     zid_g = np.sum( (C0-(np.exp(mu_g0)))**2/( ((sigma_g0)) ),axis=1)
50     return zid_g
51
52 def SAM_g_ZID(A,B):
53     row, column, feature= A.shape
54     nPixel=row*column
55     sam = np.zeros([1,nPixel])
56     Ac = A.reshape(nPixel,feature)
57     Bc = B.reshape(nPixel,feature)
58     for i in range(nPixel):
59         sam[0,i] = SAM(Ac[i,:], Bc[i,:])
```

```

60
61     zid =(ZID_g_mod(A,B))
62     sin_angle = nor01( np.tan( sam ) )
63     zidj = nor01(zid)
64     sam_zid= np.prod([[sin_angle[0,:],zidj]],axis=1)
65
66     return sam_zid
67
68
69 def OA_K(cnf):
70     index = np.nonzero(cnf)
71     TN, FP, FN, TP=cnf[index]
72     OA = (TP+TN)/(TP+TN+FP+FN)
73     p = ((TP + FP)*(TP+FN)+(TN+FN)*(TN+FP))/(TP + TN + FP + FN)**2
74     Kappa = (OA-p)/(1-p)
75     return OA,Kappa
76
77 def Binarize1(M):
78     Temp = np.copy(M)
79     Temp2 = np.copy(Temp)
80     Temp3 = np.copy(Temp)
81     Temp4 = np.copy(Temp)
82     Temp5 = np.copy(Temp)
83     Temp6 = np.copy(Temp)
84
85     Temp2[Temp>=0.2]=1
86     Temp2[Temp<0.2]=0
87
88     Temp3[Temp>=0.3]=1
89     Temp3[Temp<0.3]=0
90
91     Temp4[Temp>=0.4]=1
92     Temp4[Temp<0.4]=0
93
94     Temp5[Temp>=0.5]=1
95     Temp5[Temp<0.5]=0
96
97     Temp6[Temp>=0.6]=1
98     Temp6[Temp<0.6]=0
99
100    MediaM = (Temp2+Temp3+Temp4+Temp5+ Temp6)/2.0
101
102    return MediaM

```

Euclidean distance

In [12]:

```
1 diff_matH = H1-H2
2 EuH = np.zeros([1,m1*n1])
3 for i in range(m1*n1):
4     EuH[0,i] = np.linalg.norm(diff_matH[i,:])
5
6
7 diff_matU = U1-U2
8 EuU = np.zeros([1,mu1*nu1])
9 for i in range(mu1*nu1):
10    EuU[0,i] = np.linalg.norm(diff_matU[i,:])
11
12
13 diff_matR = R1-R2
14 EuR = np.zeros([1, mr1*nr1])
15 for i in range(mr1*nr1):
16    EuR[0,i] = np.linalg.norm(diff_matR[i,:])
17
```

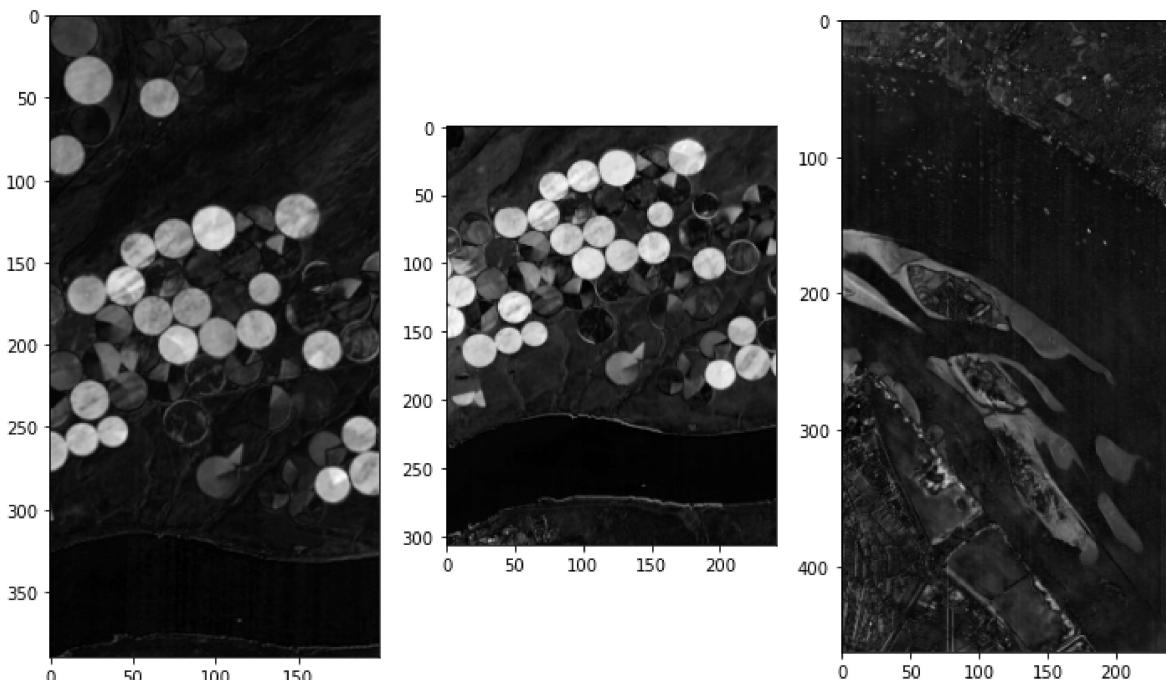
In [14]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 fig.suptitle('Euclidean distance')
3 ax1.imshow(EuH.reshape(m1,n1),cmap = plt.cm.gray)
4 ax2.imshow(EuU.reshape(mu1,nu1),cmap = plt.cm.gray)
5 ax3.imshow(EuR.reshape(mr1,nr1),cmap = plt.cm.gray)
6
```

Out[14]:

<matplotlib.image.AxesImage at 0x2581e0fb788>

Euclidean distance



We apply binarization:

- We scale the matrix values between 0 and 1
- We apply several thresholds

In [15]:

```
1 EuH = Scale(EuH)
2
3 EuU = Scale(EuU)
4
5 EuR = Scale(EuR)
```

In [16]:

```
1 MediaEuH = Binarize1(EuH)
2 MediaEuH[MediaEuH>=1.0]=1.0
3 MediaEuH[MediaEuH<1.0]=0.0
4 MediaEuH = MediaEuH.astype(int)
5
6 MediaEuU = Binarize1(EuU)
7 MediaEuU[MediaEuU>=1.0]=1.0
8 MediaEuU[MediaEuU<1.0]=0.0
9 MediaEuU = MediaEuU.astype(int)
10
11 MediaEuR = Binarize1(EuR)
12 MediaEuR[MediaEuR>=1.0]=1.0
13 MediaEuR[MediaEuR<1.0]=0.0
14 MediaEuR = MediaEuR.astype(int)
```

SAMZID

In [17]:

```
1 Hssz = SAM_ZID(H1.reshape(m1,n1,k1),H2.reshape(m2,n2,k2))
2
3 Ussz = SAM_ZID(U1.reshape(mu1,nu1,ku1),U2.reshape(mu2,nu2,ku2))
4
5 Rssz = SAM_ZID(R1.reshape(mr1, nr1, kr1),R2.reshape(mr2, nr2, kr2))
```

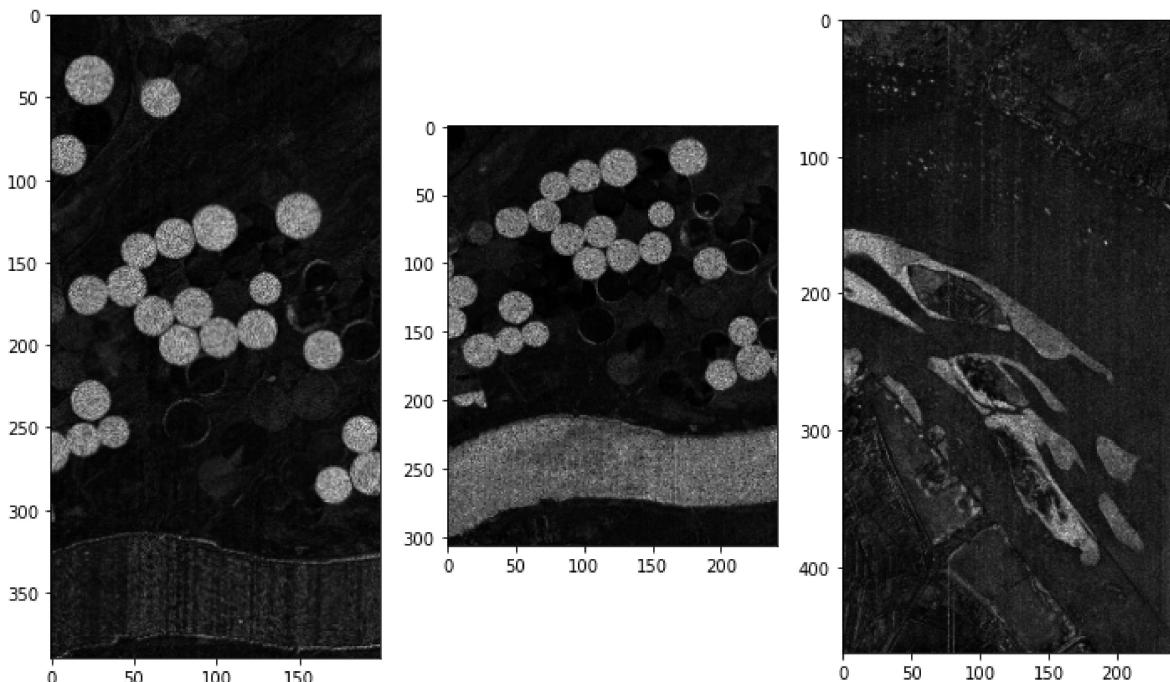
In [18]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 fig.suptitle('SAM-ZID distance')
3 ax1.imshow(Hssz.reshape(m1,n1),cmap = plt.cm.gray)
4 ax2.imshow(Ussz.reshape(mu1,nu1), cmap = plt.cm.gray)
5 ax3.imshow(Rssz.reshape(mr1, nr1), cmap = plt.cm.gray)
```

Out[18]:

<matplotlib.image.AxesImage at 0x2581de16dc8>

SAM-ZID distance



In [19]:

```
1 Hssz = Scale(Hssz)
2
3 Ussz = Scale(Ussz)
4
5 Rssz = Scale(Rssz)
```

In [20]:

```
1 MediaHssz = Binarize1(Hssz)
2 MediaHssz[MediaHssz>=1.0]=1.0
3 MediaHssz[MediaHssz<1.0]=0.0
4 MediaHssz = MediaHssz.astype(int)
5
6
7 MediaUssz = Binarize1(Ussz)
8 MediaUssz[MediaUssz>=1.0]=1.0
9 MediaUssz[MediaUssz<1.0]=0.0
10 MediaUssz = MediaUssz.astype(int)
11
12
13 MediaRssz = Binarize1(Rssz)
14 MediaRssz[MediaRssz>=1.0]=1.0
15 MediaRssz[MediaRssz<1.0]=0.0
16 MediaRssz = MediaRssz.astype(int)
```

SAM-MEAN

In [21]:

```
1 HsM = SAM_MEAN(H1.reshape(m1,n1,k1), H2.reshape(m2,n2,k2))
2
3 UsM = SAM_MEAN(U1.reshape(mu1,nu1,ku1), U2.reshape(mu2,nu2,ku2))
4
5 RsM = SAM_MEAN(R1.reshape(mr1, nr1, kr1), R2.reshape(mr2, nr2, kr2))
```

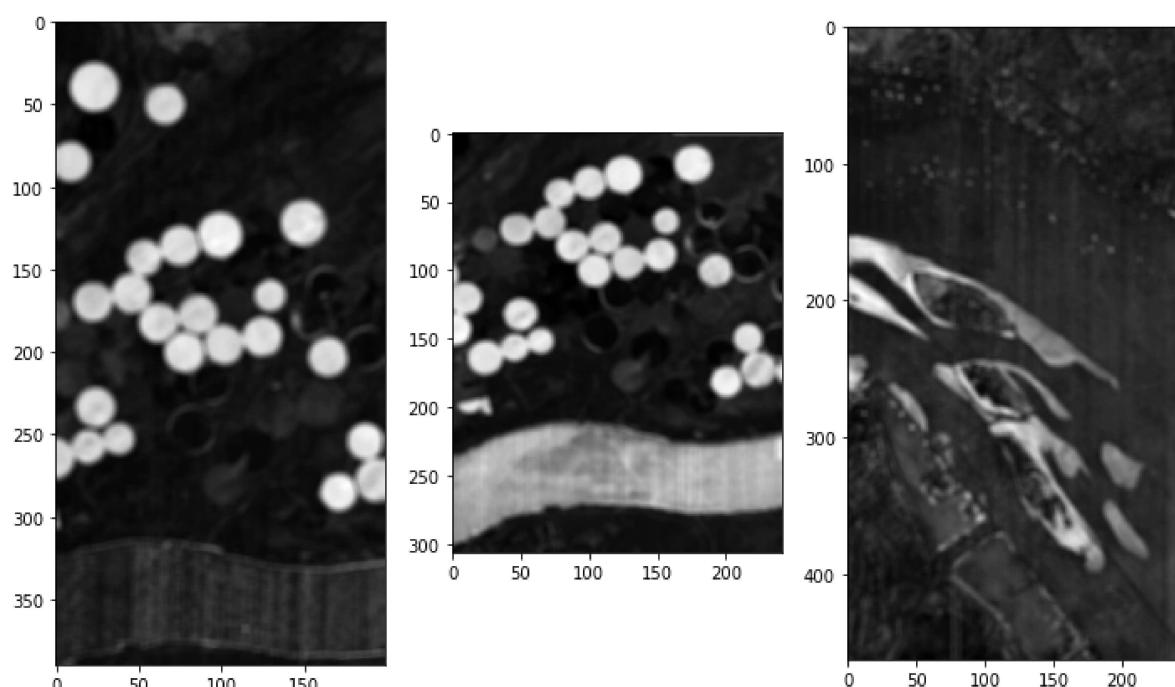
In [23]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 fig.suptitle('SAM-MEAN distance')
3 ax1.imshow(HsM, cmap = plt.cm.gray)
4 ax2.imshow(UsM, cmap = plt.cm.gray)
5 ax3.imshow(RsM, cmap = plt.cm.gray)
```

Out[23]:

<matplotlib.image.AxesImage at 0x258264b2e48>

SAM-MEAN distance



In [24]:

```
1 HsM = Scale(HsM)
2 UsM = Scale(UsM)
3
4 RsM = Scale(RsM)
```

In [25]:

```
1 MediaHsM = Binarize1(HsM)
2 MediaHsM[MediaHsM>=1.0]=1.0
3 MediaHsM[MediaHsM<1.0]=0.0
4 MediaHsM = MediaHsM.astype(int)
5
6
7 MediaUsM = Binarize1(UsM)
8 MediaUsM[MediaUsM>=1.0]=1.0
9 MediaUsM[MediaUsM<1.0]=0.0
10 MediaUsM = MediaUsM.astype(int)
11
12
13 MediaRsM = Binarize1(RsM)
14 MediaRsM[MediaRsM>=1.0]=1.0
15 MediaRsM[MediaRsM<1.0]=0.0
16 MediaRsM = MediaRsM.astype(int)
```

In [26]:

```
1 '''To uncomment only if chunks of codes are run not in the prescribed order, as dimensions might be different'''
2
3 #[m1,n1,k1] = her1.shape
4
5 #H1 = np.reshape(her1,[m1*n1,k1])
6
7 #[m2,n2,k2] = her2.shape
8
9 #H2 = np.reshape(her2,[m2*n2,k2])
```

Out[26]:

'To uncomment only if chunks of codes are run not in the prescribed order, as dimensions might be different'

SMSADM

In [27]:

```
1 Hsc = newSSCC(H1.reshape(m1,n1,k1), H2.reshape(m2,n2,k2))
2 Usc = newSSCC(U1.reshape(mu1,nu1,ku1), U2.reshape(mu2,nu2,ku2))
3
4 Rsc = newSSCC(R1.reshape(mr1, nr1, kr1), R2.reshape(mr2, nr2, kr2))
```

...

In [28]:

```
1 # The images are not preprocessed, SMSADM might produces some spurious "0/0"
2 Hsc[np.isnan(Hsc)]=0
3
4 Usc[np.isnan(Usc)]=0
5
6 Rsc[np.isnan(Rsc)]=0
7
```

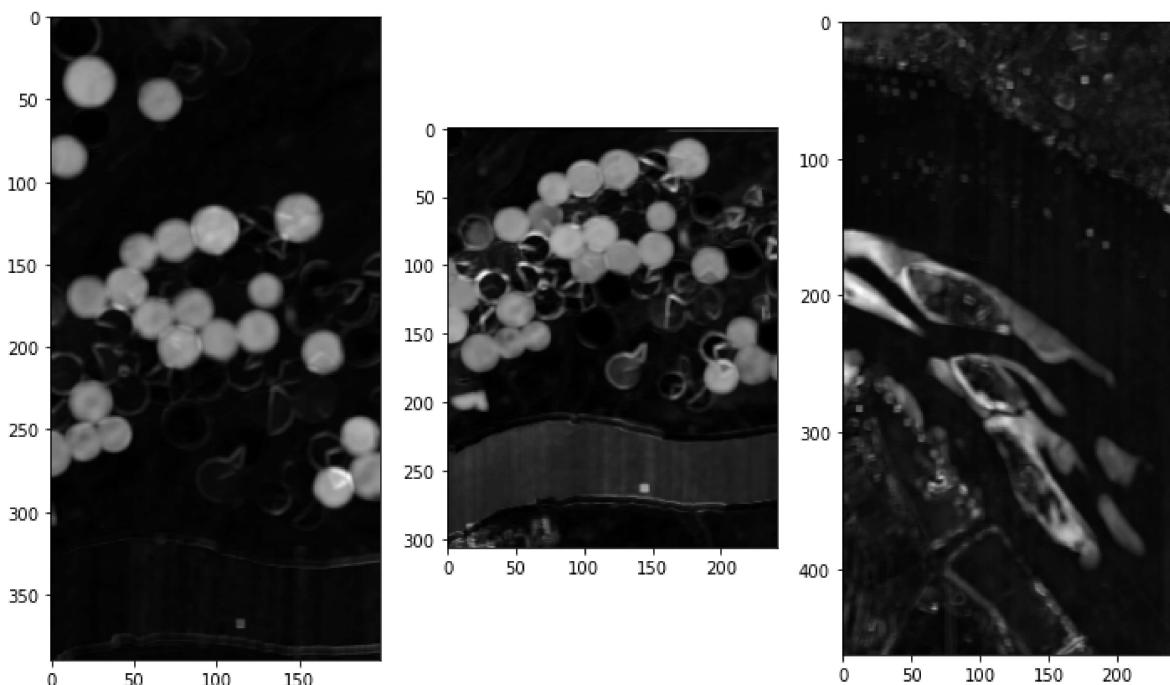
In [30]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 fig.suptitle('SMSADM distance')
3 ax1.imshow(Hsc.reshape(m1,n1), cmap = plt.cm.gray)
4 ax2.imshow(Usc.reshape(mu1,nu1), cmap = plt.cm.gray)
5 ax3.imshow(Rsc.reshape(mr1, nr1), cmap = plt.cm.gray)
```

Out[30]:

<matplotlib.image.AxesImage at 0x25826a0a348>

SMSADM distance



In [31]:

```
1 Hsc = Scale(Hsc)
2
3 Usc = Scale(Usc)
4
5 Rsc = Scale(Rsc)
```

In [32]:

```
1 MediaHsc = Binarize1(Hsc)
2 MediaHsc[MediaHsc>=1.0]=1.0
3 MediaHsc[MediaHsc<1.0]=0.0
4 MediaHsc = MediaHsc.astype(int)
5
6 MediaUsc = Binarize1(Usc)
7 MediaUsc[MediaUsc>=1.0]=1.0
8 MediaUsc[MediaUsc<1.0]=0.0
9 MediaUsc = MediaUsc.astype(int)
10
11
12 MediaRsc = Binarize1(Rsc)
13 MediaRsc[MediaRsc>=1.0]=1.0
14 MediaRsc[MediaRsc<1.0]=0.0
15 MediaRsc = MediaRsc.astype(int)
```

|| · ||₁

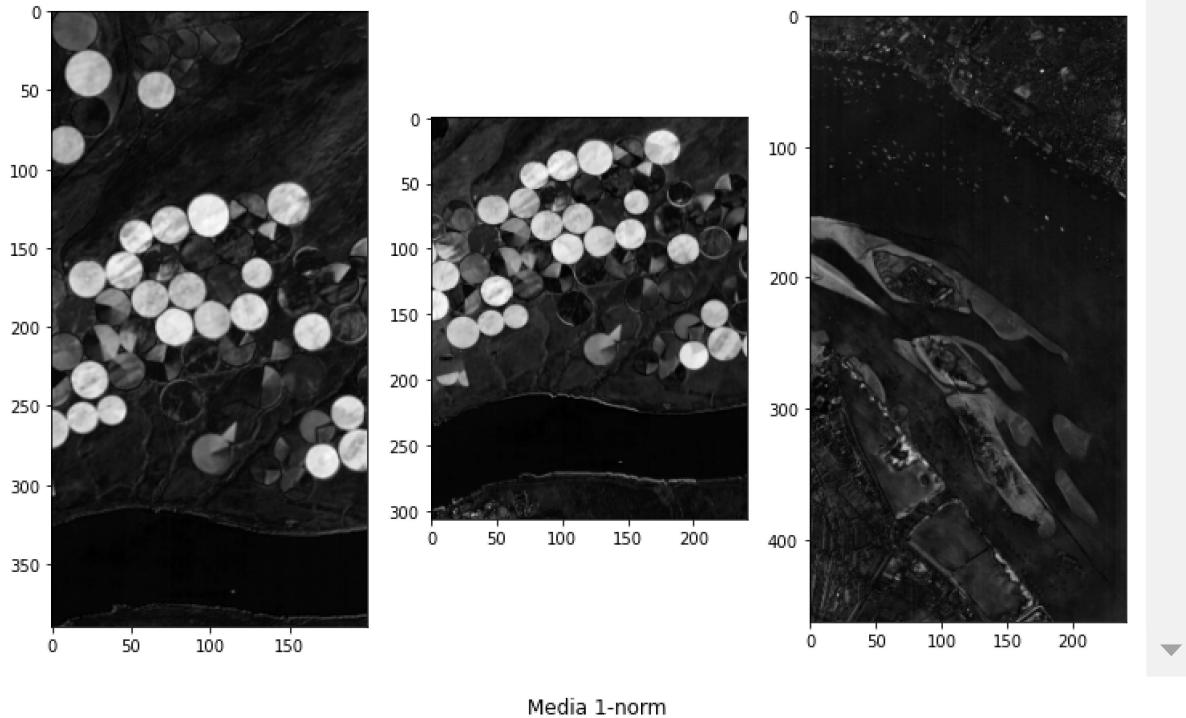
In [34]:

```
1 H1norm = np.zeros(m1*n1)
2 U1norm = np.zeros(mu1*nu1)
3 R1norm = np.zeros(mr1*nr1)
4
5 for i in range(m1*n1):
6     H1norm[i]= np.sum(abs(H1[i,:]-H2[i,:]))
7 for i in range(mu1*nu1):
8     U1norm[i]= np.sum(abs(U1[i,:]-U2[i,:]))
9 for i in range(mr1*nr1):
10    R1norm[i]= np.sum(abs(R1[i,:]-R2[i,:]))
11
12
13 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
14 fig.suptitle('1-norm')
15 ax1.imshow(H1norm.reshape(m1,n1),cmap = plt.cm.gray)
16 ax2.imshow(U1norm.reshape(mu1,nu1), cmap = plt.cm.gray)
17 ax3.imshow(R1norm.reshape(mr1,nr1), cmap = plt.cm.gray)
18
19
20 H1norm = Scale(H1norm)
21 U1norm = Scale(U1norm)
22 R1norm = Scale(R1norm)
23
24
25 MediaH1norm = Binarize1(H1norm)
26 MediaH1norm[MediaH1norm>=1.0]=1.0
27 MediaH1norm[MediaH1norm<1.0]=0.0
28 MediaH1norm = MediaH1norm.astype(int)
29
30
31 MediaU1norm = Binarize1(U1norm)
32 MediaU1norm[MediaU1norm>=1.0]=1.0
33 MediaU1norm[MediaU1norm<1.0]=0.0
34 MediaU1norm = MediaU1norm.astype(int)
35
36
37 MediaR1norm = Binarize1(R1norm)
38 MediaR1norm[MediaR1norm>=1.0]=1.0
39 MediaR1norm[MediaR1norm<1.0]=0.0
40 MediaR1norm = MediaR1norm.astype(int)
41
42 #####
43
44 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
45 fig.suptitle('Media 1-norm')
46 ax1.imshow(MediaH1norm.reshape(m1,n1),cmap = plt.cm.gray)
47 ax2.imshow(MediaU1norm.reshape(mu1,nu1), cmap = plt.cm.gray)
48 ax3.imshow(MediaR1norm.reshape(mr1,nr1), cmap = plt.cm.gray)
```

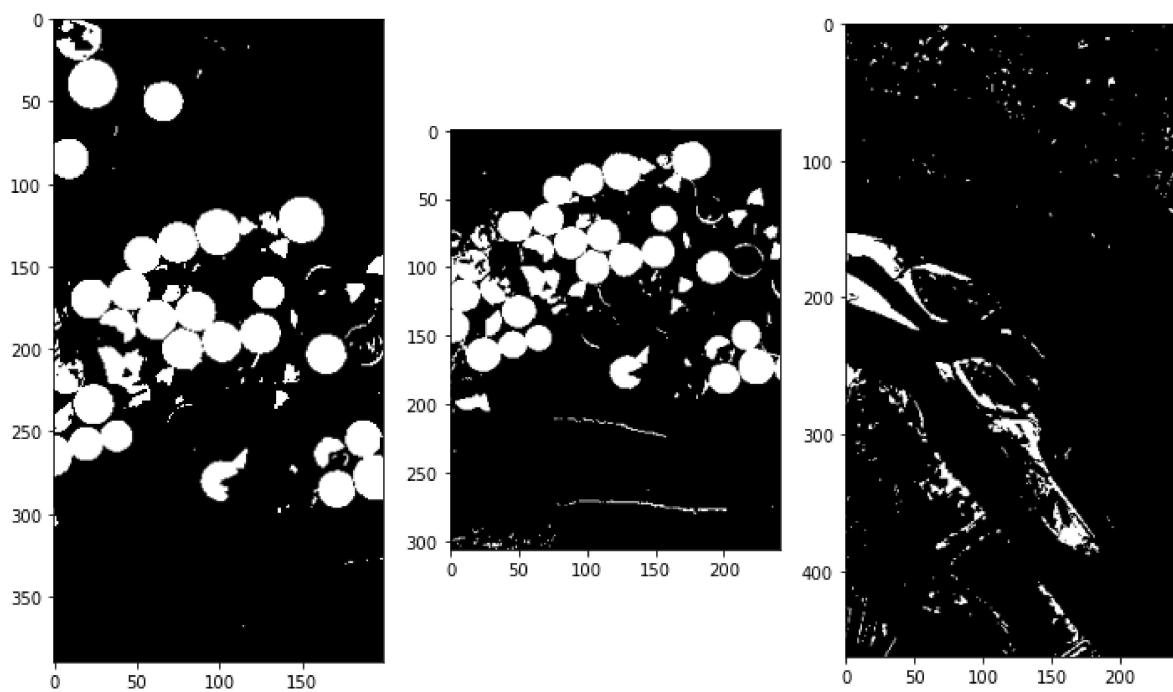
Out[34]:

```
<matplotlib.image.AxesImage at 0x2581e328448>
```

1-norm



Media 1-norm

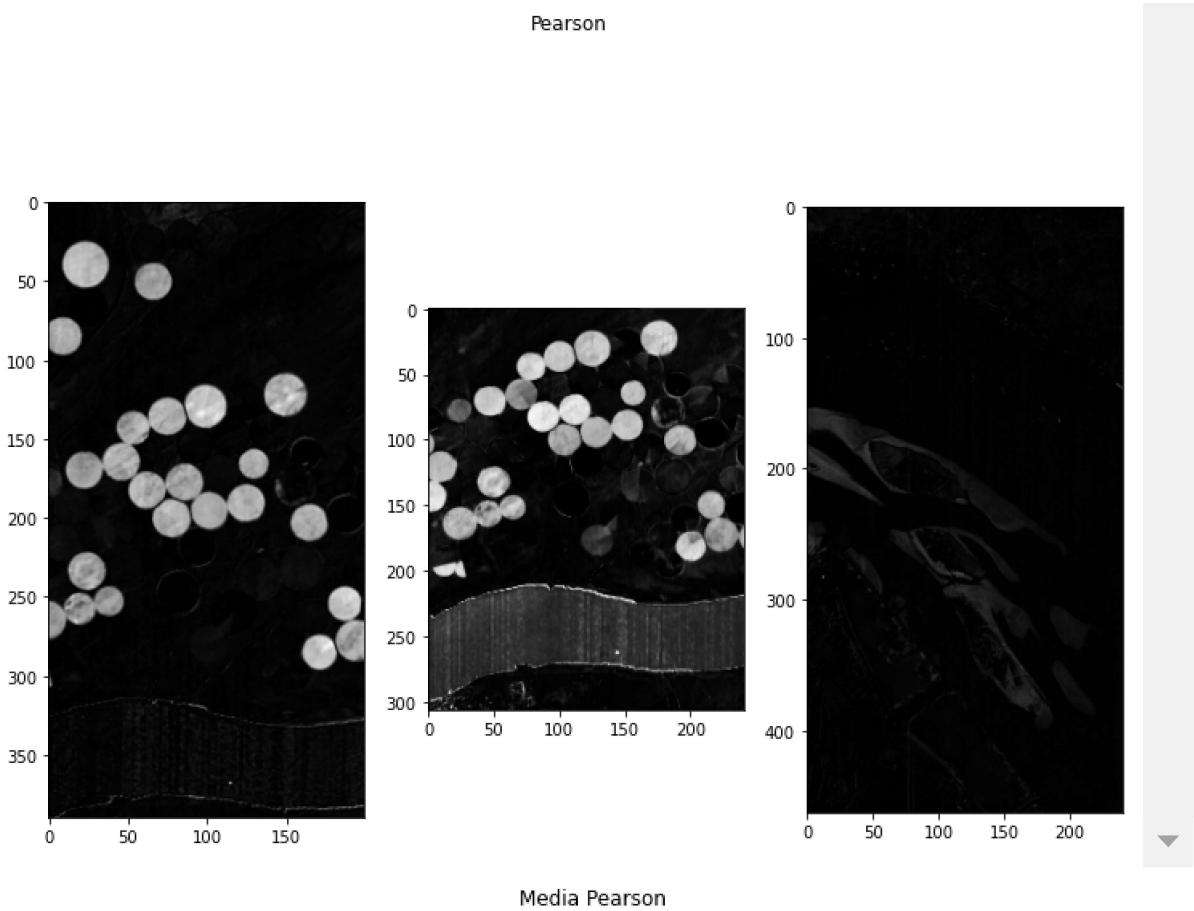


In [36]:

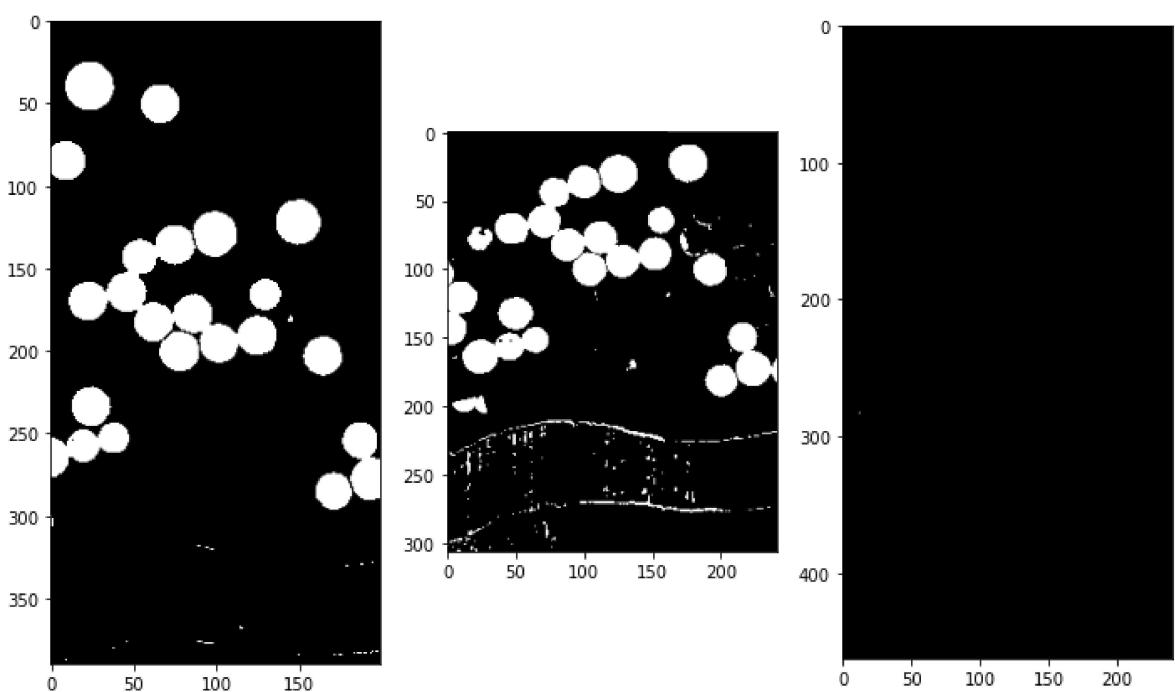
```
1 Hpr = np.zeros(m1*n1)
2 Upr = np.zeros(mu1*nu1)
3 Rpr = np.zeros(mr1*nr1)
4
5 for i in range(m1*n1):
6     Hpr[i],sH = stats.pearsonr((H1[i,:]),(H2[i,:]))
7 for i in range(mu1*nu1):
8     Upr[i],sU = stats.pearsonr((U1[i,:]),(U2[i,:]))
9 for i in range(mr1*nr1):
10    Rpr[i],sR = stats.pearsonr((R1[i,:]),(R2[i,:]))
11
12
13 Hpr = 1-abs(Hpr)
14 Upr = 1-abs(Upr)
15 Rpr = 1-abs(Rpr)
16
17
18 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
19 fig.suptitle('Pearson')
20 ax1.imshow(Hpr.reshape(m1,n1),cmap = plt.cm.gray)
21 ax2.imshow(Upr.reshape(mu1,nu1), cmap = plt.cm.gray)
22 ax3.imshow(Rpr.reshape(mr1,nr1), cmap = plt.cm.gray)
23
24
25 Hpr = Scale(Hpr)
26 Upr = Scale(Upr)
27 Rpr = Scale(Rpr)
28
29
30 MediaHpr = Binarize1(Hpr)
31 MediaHpr[MediaHpr>=1.0]=1.0
32 MediaHpr[MediaHpr<1.0]=0.0
33 MediaHpr = MediaHpr.astype(int)
34
35
36 MediaUpr = Binarize1(Upr)
37 MediaUpr[MediaUpr>=1.0]=1.0
38 MediaUpr[MediaUpr<1.0]=0.0
39 MediaUpr = MediaUpr.astype(int)
40
41
42 MediaRpr = Binarize1(Rpr)
43 MediaRpr[MediaRpr>=1.0]=1.0
44 MediaRpr[MediaRpr<1.0]=0.0
45 MediaRpr = MediaRpr.astype(int)
46
47 #####
48
49 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
50 fig.suptitle('Media Pearson')
51 ax1.imshow(MediaHpr.reshape(m1,n1),cmap = plt.cm.gray)
52 ax2.imshow(MediaUpr.reshape(mu1,nu1), cmap = plt.cm.gray)
53 ax3.imshow(MediaRpr.reshape(mr1,nr1), cmap = plt.cm.gray)
```

Out[36]:

```
<matplotlib.image.AxesImage at 0x258272f8088>
```



Media Pearson



In [37]:

```
#sM+MediaHpr.reshape(m1,n1)+MediaH1norm.reshape(m1,n1)+MediaHszz.reshape(m1,n1))#
diaUsc+MediaUpr.reshape(mu1,nu1)+MediaU1norm.reshape(mu1,nu1)+MediaUssz.reshape(mu1,nu1))#
diaRsM+MediaRpr.reshape(mr1, nr1)+MediaR1norm.reshape(mr1, nr1)+MediaRszz.reshape(mr1, nr1))#
```

In [38]:

```
1 nOUT_H = np.copy(OUT_H)
2 nOUT_H[nOUT_H<3]=0
3 nOUT_H[nOUT_H>=3]=1
4
5
6 nOUT_U = np.copy(OUT_U)
7 nOUT_U[nOUT_U<3]=0
8 nOUT_U[nOUT_U>=3]=1
9
10
11 nOUT_R = np.copy(OUT_R)
12 nOUT_R[nOUT_R<3]=0
13 nOUT_R[nOUT_R>=3]=1
```

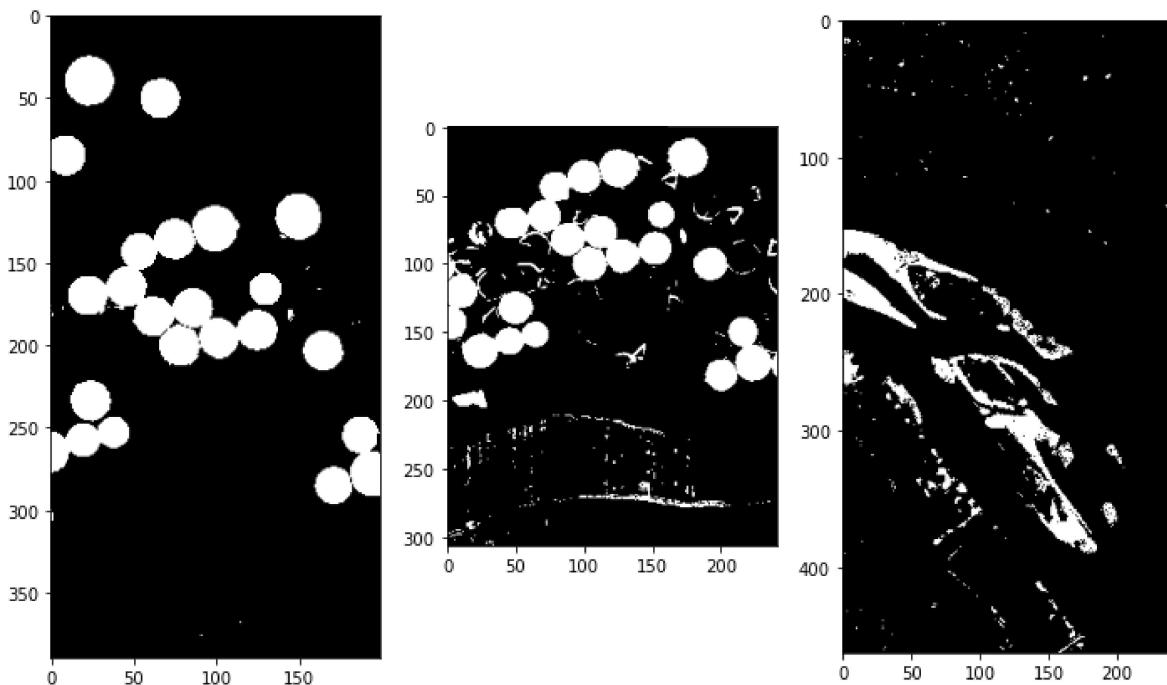
In [39]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 fig.suptitle('First Output')
3 ax1.imshow(nOUT_H.reshape(m1,n1),cmap = plt.cm.gray)
4 ax2.imshow(nOUT_U.reshape(mu1,nu1), cmap = plt.cm.gray)
5 ax3.imshow(nOUT_R.reshape(mr1,nr1), cmap = plt.cm.gray)
```

Out[39]:

<matplotlib.image.AxesImage at 0x258266fc2c8>

First Output



In [40]:

```
1 cnfH =confusion_matrix(new_gt, nOUT_H.ravel()).ravel()
2 OAH,KH = OA_K(cnfH)
3 print('\n overall accuracy Hermiston ', OAH)
4 print('\n Kappa coeff Hermiston ', KH)
5
6
7 cnfU =confusion_matrix(gtU.ravel(), nOUT_U.ravel()).ravel()
8 OAU,KU = OA_K(cnfU)
9 print('\n overall accuracy USA ', OAU)
10 print('\n Kappa coeff USA ', KU)
11
12
13 cnfR =confusion_matrix(gtR.ravel(), nOUT_R.ravel()).ravel()
14 OAR,KR = OA_K(cnfR)
15 print('\n overall accuracy River ', OAR)
16 print('\n Kappa coeff River ', KR)
17
```

```
overall accuracy Hermiston  0.9866794871794872
Kappa coeff Hermiston  0.9410218110311578
overall accuracy USA  0.9108221714625543
Kappa coeff USA  0.7164311235731688
overall accuracy River  0.9624405151322334
Kappa coeff River  0.7250442980210057
```

Post-Processing Step:

- For 'Usa' and 'River' dataset, the obtained results can be improved by using the current output as pseudo-labels to a supervised binary classifier
- For 'Hermiston' dataset, since the produced output is a very neat binary map, it is convenient to adopt a pixel-wise cleaning/noise-removal method.

Difference images:

In [41]:

```
1 imgU = abs(U1-U2)
2 imgR = abs(R1-R2)
```

1st iteration Gaussian NB

In [42]:

```
1 clfU = GaussianNB()
2 outUF = clfU.fit(imgU, nOUT_U.reshape(mu1*nu1)).predict(imgU)
3
4 clfR = GaussianNB()
5 outRF = clfR.fit(imgR, nOUT_R.reshape(mr1*nr1)).predict(imgR)
6
7
8 cnfU =confusion_matrix(gtU.ravel(), outUF).ravel()
9 OAU,KU = OA_K(cnfU)
10 print('\n overall accuracy USA ', OAU)
11 print('\n Kappa coeff USA ', KU)
12
13
14 cnfR =confusion_matrix(gtR.ravel(), outRF).ravel()
15 OAR,KR = OA_K(cnfR)
16 print('\n overall accuracy River ', OAR)
17 print('\n Kappa coeff River ', KR)
18
```

overall accuracy USA 0.9451390109073216

Kappa coeff USA 0.8341752117302464

overall accuracy River 0.9609438713782565

Kappa coeff River 0.7711179927663249

2nd iteration of Gaussian Nb

In [43]:

```
1 clfU = GaussianNB(var_smoothing=.11252e-2)#
2 outUF = clfU.fit(imgU, outUF.reshape(mu1*nu1)).predict(imgU)
3 clfR = GaussianNB(var_smoothing=1.0)
4 outRF = clfR.fit(imgR, outRF.reshape(mr1*nr1)).predict(imgR)
5
6
7 cnfU =confusion_matrix(gtU.ravel(), outUF).ravel()
8 OAU,KU = OA_K(cnfU)
9 print('\n overall accuracy USA ', OAU)
10 print('\n Kappa coeff USA ', KU)
11
12
13 cnfR =confusion_matrix(gtR.ravel(), outRF).ravel()
14 OAR,KR = OA_K(cnfR)
15 print('\n overall accuracy River ', OAR)
16 print('\n Kappa coeff River ', KR)
```

overall accuracy USA 0.9528025193615095

Kappa coeff USA 0.8630043054922464

overall accuracy River 0.9681223842341575

Kappa coeff River 0.8013886129992429

For the Hermiston dataset instead it is convenient to remove the noise by adopting a pixel wise "filter". For such aim, a morphological opening transformation is chosen.

In [44]:

```
1 def clean_map1(change_map):
2     change_map = change_map.astype(np.uint8)
3     kernel1      = np.asarray((( 0,0,1,0,0),
4                                (0,1,1,1,0),
5                                (1,1,1,1,1),
6                                (0,1,1,1,0),
7                                (0,0,1,0,0)), dtype=np.uint8)
8
9     cleanChangeMap = cv2.morphologyEx(change_map, cv2.MORPH_OPEN, kernel1)
10
11    return cleanChangeMap
```

In [45]:

```
1 CleanedH = clean_map1(nOUT_H.reshape(m1,n1))
```

In [46]:

```
1 cnfH =confusion_matrix(new_gt, CleanedH.ravel()).ravel()
2 OAH,KH = OA_K(cnfH)
3 print('\n overall accuracy Hermiston ', OAH)
4 print('\n Kappa coeff Hermiston ', KH)
```

overall accuracy Hermiston 0.9875512820512821

Kappa coeff Hermiston 0.9446715027943061

In [47]:

```
1 fig, (ax1, ax2, ax3) = plt.subplots(1, 3, figsize=(12,9))
2 ax1.imshow(CleanedH.reshape(m1,n1), cmap = plt.cm.gray)
3 ax2.imshow(outUF.reshape(mu1,nu1), cmap = plt.cm.gray)
4 ax3.imshow(outRF.reshape(mr1, nr1), cmap = plt.cm.gray)
5 plt.title('Final Output')
6
```

Out[47]:

Text(0.5, 1.0, 'Final Output')

