

The “InclusionZoneGrid” Class

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Friday 22nd March, 2013
5:08pm

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1 Introduction

When we think about building a sampling surface piece by piece from the inclusion zones of individual “Stem” objects, we assign the appropriate attribute value to each grid cell within the inclusion zone for an object, with zero values elsewhere, and then algebraically add this grid layer to the

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overall “Tract” grid. Thus, we “heap up” the inclusion zone density of the grid cells within the tract, which in the end is a discrete estimate of the sampling surface.

This class allows us to do the geometry associated with the individual “InclusionZone” objects for each “Stem” object in the population. Recall that an “InclusionZone” object has both an “ArealSampling” and “Stem” subclass as slots in its definition. For example, an object of subclass “standUpIZ” would have both a “circularPlot” class object and a “downLog” object making up the overall bounding box. There are methods for the “InclusionZoneGrid” class objects that work with each type of “InclusionZone” object. In general, the methods are all of the name `izGrid`, whose signature objects are used to dispatch the appropriate method.

In the following, we show some general constructs of the class with respect to individual subclasses of “InclusionZone” objects they are based on. Graphics play a big role in getting the idea, and each class is a little different, so several illustrations are presented. Whether a surface within an inclusion zone is constant or variable height depends on the sampling method. For example, what we term “canonical” perpendicular distance sampling (PDS) has constant height surfaces, while “omnibus” PDS has surfaces of varying height. In addition, the somewhat odd, but interesting “full chainsaw” method where the entire sausage-based inclusion zone is filled with variable-height individual chainsaw estimates is also in this latter category as are the Monte Carlo-based methods.

2 The “InclusionZoneGrid” Class

The base class is defined with the slots...

```
R> showClass('InclusionZoneGrid')
```

```
Class "InclusionZoneGrid" [package "sampSurf"]
```

```
Slots:
```

Name:	description	iz	grid	data	bbox
Class:	character	InclusionZone	RasterLayer	data.frame	matrix

```
Known Subclasses: "csFullInclusionZoneGrid"
```

2.1 Class slots

- *description*: Some descriptive text about this class.

- *iz*: An object of one of the “InclusionZone” subclasses.
- *grid*: A “RasterLayer” object.
- *data*: A data frame holding the values for each of the per unit area estimates available in the “InclusionZone” object in the columns, with rows for grid cells.
- *bbox*: The overall bounding box for the object, which includes the inclusion zone and the “Stem” subclass object plus the grid. Sometimes the inclusion zone itself includes the stem, but other times it does not.

I made a decision when designing this class to go with the slots above. A possible problem with this design is the very real possibility of people misunderstanding the class structure. This is because the grid object has values of just zero and NA. In other words, it does not store the per unit area estimates within the cells of the grid. These are stored in the `data` slot of the object and can be swapped into the `grid` slot object with a simple command...

```
R> x@grid = setValues(x@grid, x@data[,estimate])
```

where `x` is the “InclusionZoneGrid” object. Unfortunately, again this may cause problems with misunderstanding, down the line as it is going to have to be done whenever one wants an underlying `grid` with real per unit area values. An alternative to this would have been (and still could be) to use a “RasterStack” or “RasterBrick” class for the `grid` slot. This would obviate the need for the `data` slot. But it also has drawbacks, because these objects seem to be designed more for map layers that are algebraically related. I did not want people unwittingly summing layers within this object, for example, and thereby adding things like number of stems and cubic volume. I may reconsider this, however, as the latter approach does have its benefits (even though it takes more storage). Another potential drawback of the latter is that there seems to be no way to name the “layers” within a brick or stack, they simply get assigned numbers, so we’d again have to keep track of this with program code.

When plotting the object, the above substitution gets made automatically, one simply has to specify the desired attribute to plot in the `estimate` argument to the `plot` method. For example, to plot the coverage area surface, specify `estimate = 'coverageArea'` in the plot command. The default is to plot the surface for volume.

3 Example: The “standUpIZ” Class

Refer to *The “InclusionZone” Class* vignette for more information on this class.

Here we demonstrate the construction of an “InclusionZoneGrid” object from an object of class “standUpIZ”.

```

R> tra = Tract(c(x=100, y=100), cellSize = 0.5, units = 'metric',
+             description = 'a 1-hectare tract')
R> btr = bufferedTract(10, tra)
R> btr

-----
a 1-hectare tract
-----

Measurement units = metric
Area in square meters = 10000 (1 hectares)

class      : bufferedTract
dimensions : 200, 200, 40000 (nrow, ncol, ncell)
resolution : 0.5, 0.5 (x, y)
extent     : 0, 100, 0, 100 (xmin, xmax, ymin, ymax)
coord. ref. : NA
data source : in memory
names      : surf
values     : 0, 0 (min, max)

Buffer width = 10

R> dlogs = downLogs(1, container=btr@bufferRect, buttDiam=c(30,40),
+                  logLen=c(6,10), topDiams=c(0,0.5), solidTypes=c(2,4),
+                  vol2wgt=20.1, wgt2carbon=0.5)
R> sup = standUpIZ(dlogs@logs$log.1, 3)
R> izgSU = izGrid(sup, btr)

```

Here we have created a 200 by 200 cell raster grid in the form of a “Tract” object, having resolution of 0.5 meters, yielding spatial extents of 100×100 meters, (i.e., a 1 hectare tract), with origin at (0,0) meters. Then we create a buffered tract object with a 10-meter buffer, and drew a single random “downLog” object within the tract, which we used to create an object of class “standUpIZ” with a 3 meter radius for the circular plot. Finally, using the “standUpIZ” object and the underlying buffered tract grid, we create the “InclusionZoneGrid” object that will be aligned to the tract grid.

Now, in the following example we plot this object...

```
R> plot(izgSU)
```

There are two ways to generate the object which depend on how one wants the underlying grid developed. The argument `wholeIZ` determines how this is done, and defaults to `TRUE`. We can see

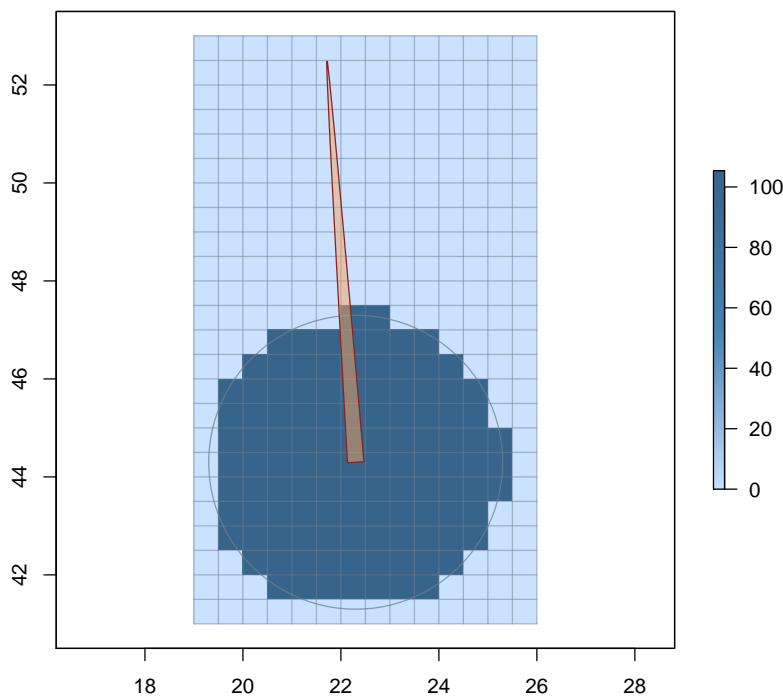


Figure 1: An “InclusionZoneGrid” object based on a “standUpIZ” object.

in Figure 1 that the underlying grid covers the entire inclusion zone plus the down log object. If we wanted to just cover the inclusion zone only, with a minimal bounding grid we would do the following (Figure 2)...

```
R> izmbgSU = izGrid(sup, btr, wholeIZ=FALSE)
R> plot(izmbgSU, gridCenters=TRUE)
```

4 On Design Motivation

Having now seen that we can make the grid object cover more than just the inclusion zone if applicable (i.e., the stem lies partially outside it), we can delve a little more into the motivation for this class. First, it is entirely possible to approach the sampling surface construction in a more brute-force manner in one of at least two ways...

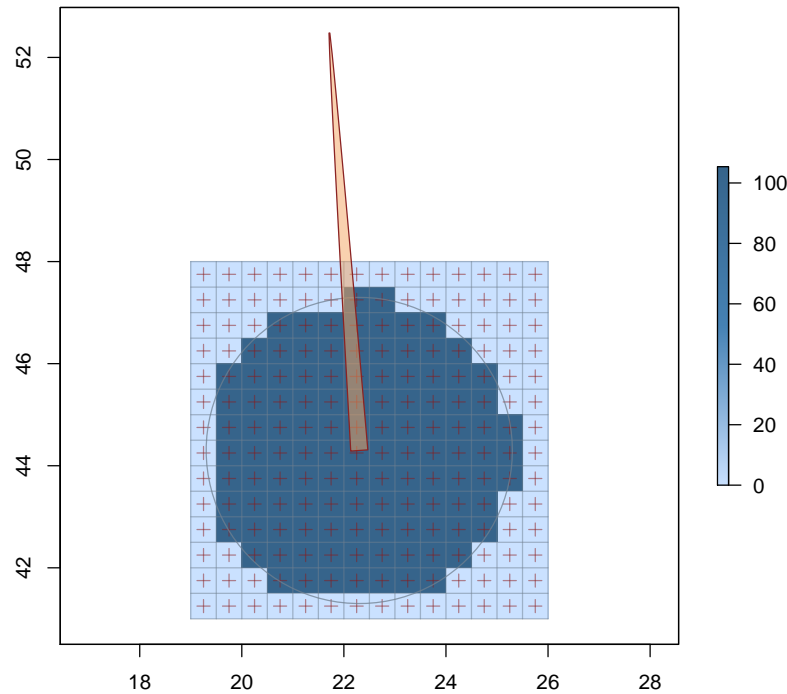


Figure 2: An “InclusionZoneGrid” object based on a “standUpIZ” object where only the actual inclusion zone is covered by the bounding grid, and grid cell centers are plotted as an option.

1. Brute-force method 1...

- Make an exact duplicate of the tract and assign zeros to all its values.
- Then overlay the inclusion zone onto this to get a mask.
- Assign the per acre values to the cells within the masked inclusion zone and zero outside.
- Algebraically add this layer to the base tract and repeat for all stems.

2. Brute-force method 2...

- Use the `rasterize` function within “raster” with `overlap='sum'` on the “InclusionZone” objects to sum them into the base tract grid.
- Repeat for all stems.

The problem with each of these approaches, even though they work, is the time it takes to implement them. In each case they are working on the entire tract and take significantly more time to

do the accumulation than overlaying onto the smaller grid within the “InclusionZoneGrid” class. This is compounded if the tract is large, or the resolution is small, which we want usually for better estimates. This, along with the thought that perhaps the following approach is simpler to understand because one can see the individual surface components graphically, is why I elected to go this route.

In slightly more detail, the steps in accumulating the surface under the “InclusionZoneGrid” scheme are...

1. Create an “InclusionZoneGrid” object.
2. Expand its grid to the extent of the tract.
3. Add this expanded grid to the tract surface.
4. Repeat for all stems.

Conceptually it is similar to the other approaches except that the actual overlay is done on a minimal bounding grid for the object, and therefore is much faster. Expanding the grid mask in the “InclusionZoneGrid” object takes little effort, and adding it is the same in all steps.

5 Example: The “sausageIZ” Class

Using the same grid and tree as above for an example with sausage sampling, we have...

```
R> saus = sausageIZ(dlogs@logs$log.1, 3)
R> izgSAUS = izGrid(saus, btr, wholeIZ=FALSE)
R> plot(izgSAUS)
```

Notice in Figure 3 that whether we specify using the whole inclusion zone or not is immaterial for sausage sampling, because the entire log is always included within the zone. Also note that the minimal bounding grid is always calculated to include the entire zone, even if there is an extra cell padding all around. This is trivial and is necessary for making sure all cells within the zone get assigned the correct value.

6 Example: The “chainSawIZ” Class

Here are a couple similar examples for the “chainSawIZ” class. Gove and Van Deusen (2011) discuss how the inclusion zone is really just a point, the center point of the circular plot that intersects

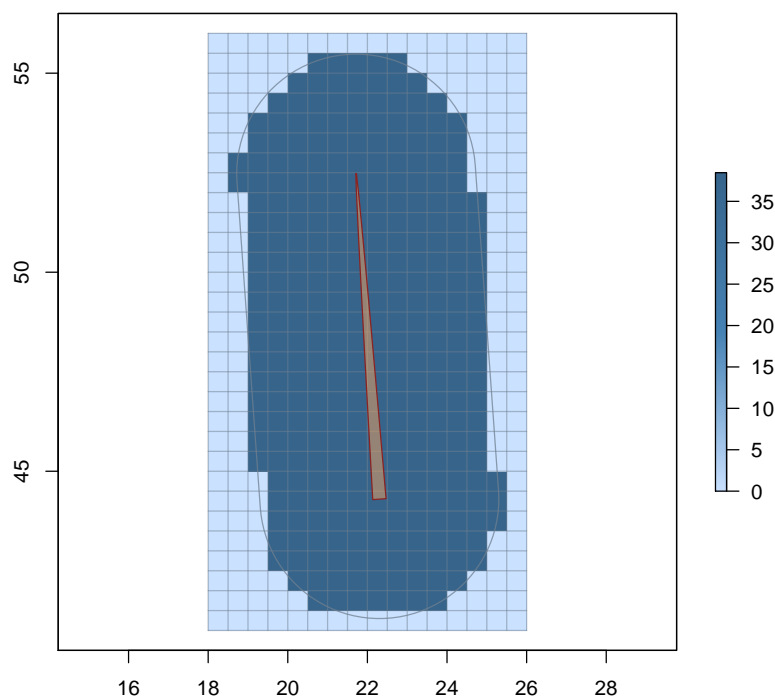


Figure 3: An “InclusionZoneGrid” object based on a “sausageIZ” object showing that the stem and inclusion zone are covered by the bounding grid.

the downed log, rather than the plot itself. Therefore, under this method, we assign the sampling surface value to only that one grid cell that contains the circular plot center point.

```
R> csaw = chainSawIZ(dlogs@logs$log.1, plotRadius = 3,
+                   plotCenter = coordinates(dlogs@logs$log.1@location)[1,] + c(1,-1))
R> izgCSaw = izGrid(csaw, btr, wholeIZ=FALSE)
R> izgCSaw
```

Object of class: InclusionZoneGrid

chainSaw grid point inclusion zone grid object

InclusionZone class: chainSawIZ


```

units of measurement:  metric

Grid class: RasterLayer
Number of grid cells = 1
Cell dimensions: (nrows=1, ncol=1)
Grid cell values**...
  gridValues Freq
1          0    1
**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...
      volume Density Length surfaceArea coverageArea biomass carbon
Min.    95.71   353.7   2042         1508         479.9    1924  961.9
1st Qu. 95.71   353.7   2042         1508         479.9    1924  961.9
Median  95.71   353.7   2042         1508         479.9    1924  961.9
Mean    95.71   353.7   2042         1508         479.9    1924  961.9
3rd Qu. 95.71   353.7   2042         1508         479.9    1924  961.9
Max.    95.71   353.7   2042         1508         479.9    1924  961.9

Encapulating bounding box...
      min      max
x 20.010685 26.009175
y 44.287258 52.478895

R> plot(izgCSaw, gridCenters=TRUE)

```

Figure 4 shows the concept for a given circular plot location showing volume in cubic meters per hectare. This clearly shows that only one grid cell gets assigned a value. Note in the above that there is only a single grid cell in the object comprising the “InclusionZoneGrid”.

We can also show the minimal bounding grid that includes the whole circular plot plus the log, as we have done in previous examples. Figure 5 presents this graphically.

```

R> izgCSaw = izGrid(csaw, btr, wholeIZ=TRUE)
R> plot(izgCSaw, gridCenters=TRUE, estimate='Density',
+       showPlotCenter=TRUE, izCenterColor = 'white')

```

As with the other figures, the overall minimal bounding grid in Figure 5 has all grid cells other than the one at the center of the circular plot set to zero. Therefore, doing any subsequent map algebra will have no effect on the sampling surface using this enlarged grid. Showing this minimal bounding grid is more an effort to help illustrate the underlying concepts.

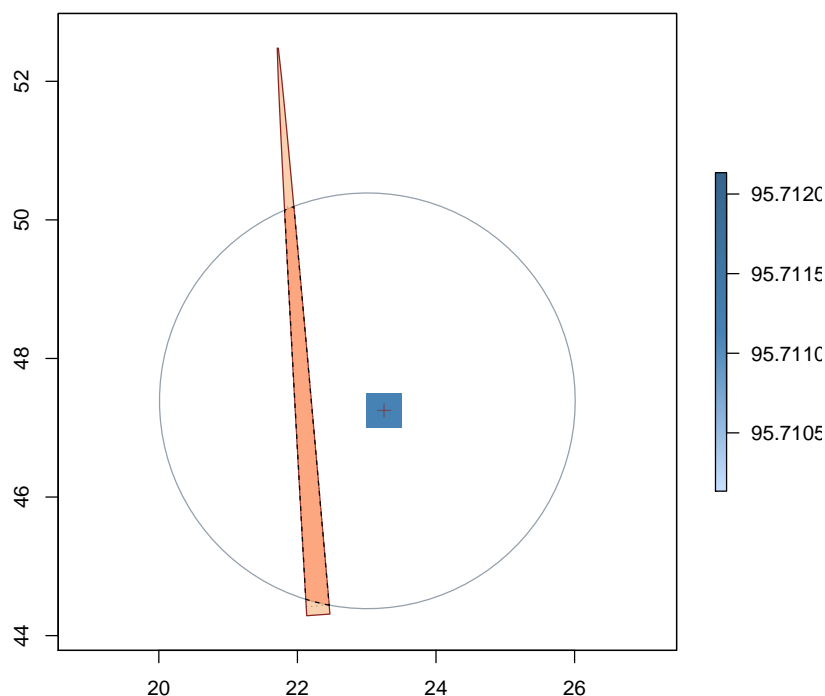


Figure 4: An “InclusionZoneGrid” object based on a “chainSawIZ” object showing that the inclusion zone is only a single point, and therefore is assigned to just one grid cell.

It is especially important to recognize that the center point of the circular plot does not necessarily lie at the center of any given grid cell. Depending upon the cell resolution used, this can make the placement of this respective cell look “off-center” with respect to the circular plot’s perimeter itself. It is only true that the center point falls somewhere within the inclusion zone grid cell, which could even be right on the edge. This is shown in Figure 5 where we use a white cross for the circular plot center, and is demonstrated below in terms of actual coordinates...

```
R> cpt = perimeter(csaw, whatSense='point') #circular plot centerpoint
R> cn = cellFromXY(izgCSaw@grid, cpt)      #cell number for plot center point
R> xy = xyFromCell(izgCSaw@grid, cn)       #cell center point
R> rbind(coordinates(cpt), xy)
```

```
      x      y
[1,] 23.009175 47.388784
```

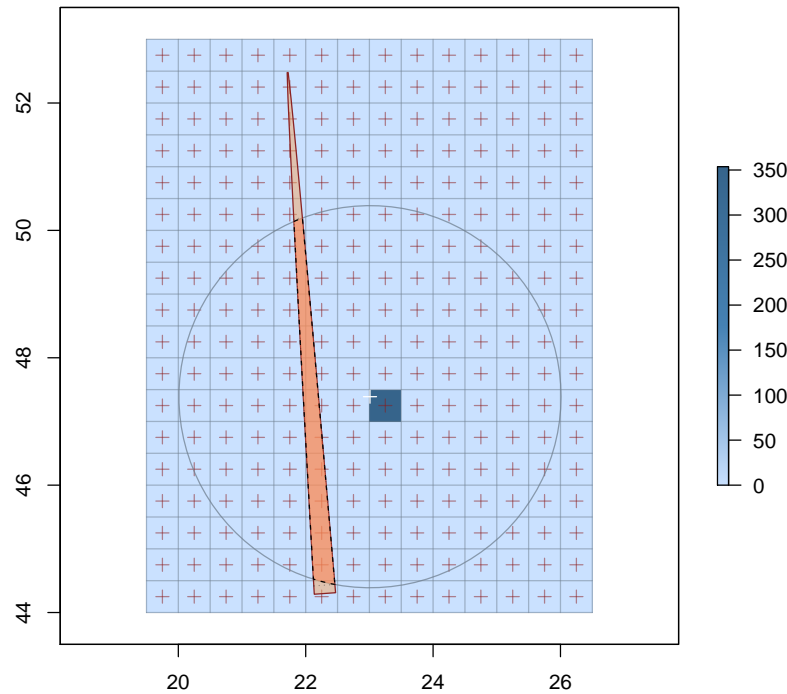


Figure 5: An “InclusionZoneGrid” object based on a “chainSawIZ” object showing the minimal bounding grid for the entire inclusion zone object; this also illustrates that the inclusion zone is only a single point, since only one grid cell is non-zero valued in terms of number of stems per unit area estimate.

[2,] 23.250000 47.250000

6.1 Snapping to the grid

As another example, suppose we wanted to develop a figure that shows essentially the same depiction as in Figure 5, but also including the overall sausage inclusion zone, and the plot center exactly aligned to a grid cell center. First we would make a “Tract” object that just holds the sausage inclusion zone object, the log, and the chainsaw inclusion zone object (complete with plot radius as in Figure 5). We can use the above steps to advantage to snap the plot centerpoint to the grid as follows...

```

R> xyExtent = c(x=10, y=10)
R> tra2 = Tract(xyExtent, cellSize=0.5)
R> dl = downLog(buttDiam=40, topDiam=15, logLen=6.5, logAngle=pi/4,
+             centerOffset=xyExtent/2 )
R> cn = cellFromXY(tra2, c(x=6.5, y=4.5))
R> (cpt = xyFromCell(tra2, cn)[,,drop=TRUE]) #coerce to vector from matrix

```

```

      x      y
6.75 4.25

```

```

R> izCS = chainSawIZ(dl, plotRadius = 2, plotCenter = cpt) #cell-based chainsaw iz
R> izgCS = izGrid(izCS, tra2)                               #and chainsaw iz grid object
R> hiz = heapIZ(izgCS, tra2)                                #heap it into the tract object
R> izSaus = sausageIZ(dl, plotRadius=2)                     #overall sausage inclusion zone

```

We use the `heapIZ` method in the above to “heap” the “InclusionZoneGrid” object for the single grid cell corresponding to the chainsaw method at that point, onto the tract. The rest of the idea behind this should be fairly standard and is covered in more detail in the vignettes for the respective objects.

To plot this object, we need to basically build it up from scratch, the result is shown in Figure 6...

```

R> plot(hiz, axes=TRUE, gridLines=TRUE)
R> plot(dl, add=TRUE)
R> plot(izSaus, add=TRUE, izColor=NA, lty='dashed', izBorder='gray40')
R> plot(izCS, add=TRUE, izColor=NA, showPlotCenter=TRUE,
+      izCenterColor='white', ltyBolt='solid')

```

7 The “csFullInclusionZoneGrid” Class

Gove and Van Deusen (2011) describe a certain protocol for the chainsaw method that leads directly to the sausage method. They also show by simulation how the chainsaw method is biased for whole-log attributes, because the full inclusion zone for the log is the sausage zone under this particular protocol. To show this, every grid point within the sausage inclusion zone has to be estimated individually with its midpoint acting as the center of the circular plot, and then applying the chainsaw method to that plot. Again, this is repeated for every grid cell within the sausage inclusion zone.

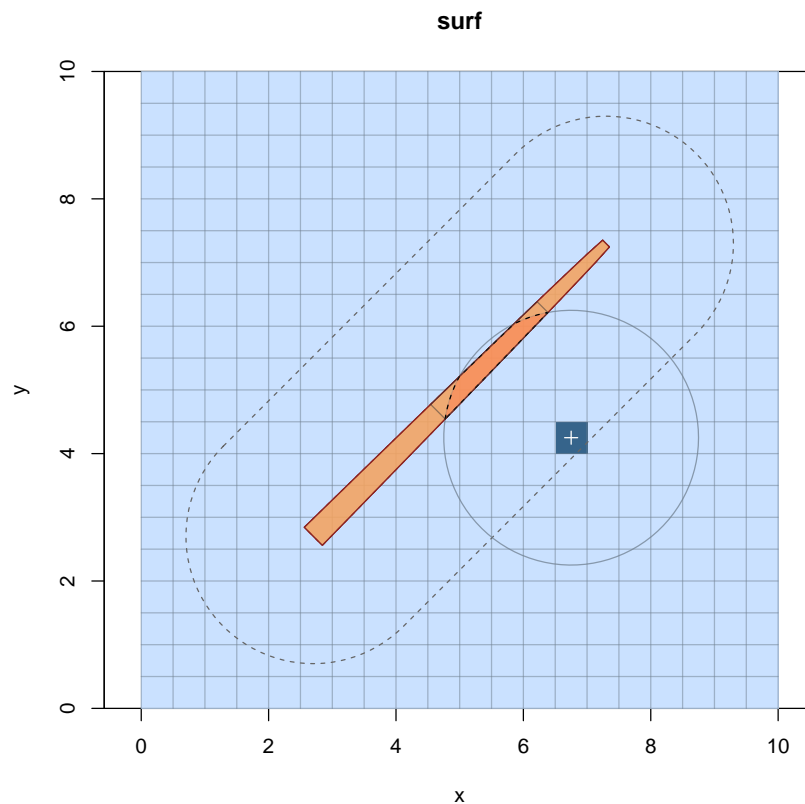


Figure 6: A built-up plot showing not only the “InclusionZoneGrid” object for one cell of the chainsaw method, but also the sausage object inclusion zone as would be determined by protocol 1 of Gove and Van Deusen (2011).

This necessitates a new class, actually a subclass of “InclusionZoneGrid” with one extra slot, and some more validity checking, as well as a new constructor for the objects. The extra slot is just used to store the result of *each* “chainSawIZ” object applied to each of the internal inclusion zone grid cells.

The class is defined with the slots...

```
R> showClass('csFullInclusionZoneGrid')
```

```
Class "csFullInclusionZoneGrid" [package "sampSurf"]
```

```
Slots:
```

Name:	chiz	description	iz	grid	data
Class:	list	character	InclusionZone	RasterLayer	data.frame

Name:	bbox
Class:	matrix

Extends: "InclusionZoneGrid"

7.1 Class slots

- *chiz*: This is a list object containing NAs for cells outside the inclusion zone, but containing the full set of “InclusionZoneGrid” objects corresponding to each grid cell within the inclusion zone. As mentioned above, the grid cell center is used as the center point of the circular plot that defines the chainsaw intersection with the log.

The nice thing about the subclass extension for this new object is that only one slot was added; therefore, all of the functions that work on “InclusionZoneGrid” objects will also work on objects of this new class “csFullInclusionZoneGrid”. These include the `print`, `show`, `summary`, and `plot` routines.

In addition, because each of the components of the list in `chiz` is of class “InclusionZoneGrid” (or NA), we can apply any of the methods for that class on the individual slots. For example, we can plot them as in Figure 4, and look at how the chainsaw method works as we step from one cell to the next, showing the intersections of the circular plots with the log.

7.2 Object Construction and Plotting

Now, object construction takes quite a while because it has to compute the chainsaw intersections, etc., for each internal sausage grid cell. So here we use an existing object to demonstrate the idea. In the following, we show how to make an object of class “csFullInclusionZoneGrid” using its constructor, but do not evaluate it (we use the existing object instead); the steps leading to its creation are also shown...

```
R> btLog = sampleLogs(1, buttDiam=c(30,40), sampleRect=buffTr@bufferRect,
+                   logLen=c(4,6), topDiams=c(0, 0.5) )
R> btLog = downLogs(btLog)
R> btLog = btLog@logs$log.1
R> btLog.sa = sausageIZ(btLog, 3)
R> btLog.izgsa = izGrid(btLog.sa, buffTr)
R> btLog.izgFCS = izGridCSFull(btLog.izgsa, buffTr)
```

where `buffTr` is essentially the same as `btr` used in the previous examples.

```
R> btLog.izgFCS
```

```
Object of class: csFullInclusionZoneGrid
```

```
-----
Full chainSaw-sausage inclusion zone grid object
-----
```

```
InclusionZone class: sausageIZ
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 441
```

```
Cell dimensions: (nrows=21, ncol=21)
```

```
Grid cell values**...
```

```
  gridValues Freq
1           0  232
2        <NA>  209
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	0.1245	353.7	18.81	4.467	1.167	2.714	1.357
1st Qu.	21.1320	353.7	470.52	383.120	121.240	460.670	230.340
Median	65.9190	353.7	892.43	846.490	268.960	1437.000	718.510
Mean	66.4250	353.7	901.40	843.110	267.920	1448.100	724.040
3rd Qu.	110.4400	353.7	1322.20	1283.000	407.420	2407.700	1203.800
Max.	138.3300	353.7	1775.50	1751.300	556.470	3015.500	1507.800

```
Encapulating bounding box...
```

```
  min  max
x 69.0 79.5
y 68.5 79.0
```

One thing to note in particular, is that with the exception of density in the printed summary of the object above, the summary statistics vary here because the grid cells are composed of individual chainsaw estimates; this is not true for methods where the cells internal to the inclusion zone only take a single constant value (e.g., stand-up, sausage, point relascope, etc.).

And plotting the object is as usual...

```
R> plot(btLog.izgFCS, gridCenters=TRUE, showNeedle=TRUE)
```

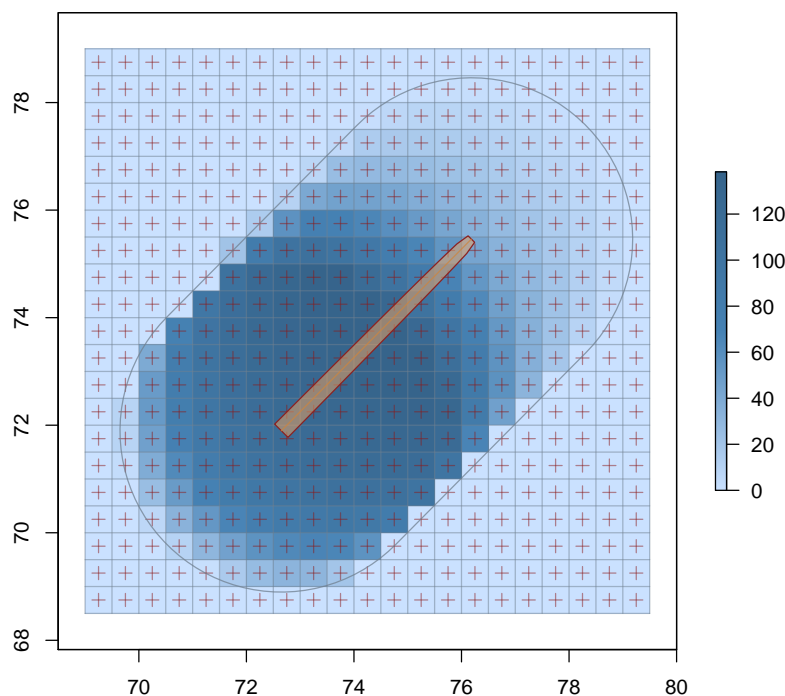


Figure 7: A “csFullInclusionZoneGrid” object based on a “sausageIZ” object.

As mentioned above, because the `chiz` slot contains a list of “InclusionZoneGrid” objects, for each grid cell within the inclusion zone, or `NA` for grid cells outside the zone, we can step through the internal cells one at a time, looking at summaries or plotting them. One way to do this would be the following...

```
R> cdx = ifelse(is.na(btLog.izgFCS@chiz), FALSE, TRUE)
R> cs1 = btLog.izgFCS@chiz[cdx]
R> length(cs1)
```

```
[1] 232
```

```
R> sapply(cs1[1:4], class)
```



```

            izgCS.34            izgCS.35            izgCS.36            izgCS.37
"InclusionZoneGrid" "InclusionZoneGrid" "InclusionZoneGrid" "InclusionZoneGrid"

```

Again, we could then plot the slivers we are interested in, stepping through to see how the chainsaw method slices the log up for each individual grid cell.

8 Example: The “pointRelascopeIZ” Class

Here we present an example for the point relascope sampling method (Gove et al. 1999, Gove et al. 2001)...

```
R> (angle = .StemEnv$rad2Deg(2*atan(1/2)))
```

```
[1] 53.130102
```

```

R> prs.as = pointRelascope(angle, units='metric')
R> prs.iz = pointRelascopeIZ(dlogs@logs$log.1, prs=prs.as)
R> (izgPRS = izGrid(prs.iz, btr))

```

```
Object of class: InclusionZoneGrid
```

```
-----
pointRelascopeIZ inclusion zone grid object
-----
```

```

InclusionZone class: pointRelascopeIZ
units of measurement: metric

```

```

Grid class: RasterLayer
Number of grid cells = 782
Cell dimensions: (nrows=23, ncol=34)
Grid cell values**...

```

```

    gridValues Freq
1           0  560
2        <NA>  222

```

****Note:** data slot values get swapped with zero-valued grid cells as necessary.

```

Per unit area estimates in the data slot (for cells inside IZ only)...
    volume Density Length surfaceArea coverageArea biomass carbon

```

Min.	21.05	70.65	579.4	357.8	113.9	423.1	211.6
1st Qu.	21.05	70.65	579.4	357.8	113.9	423.1	211.6
Median	21.05	70.65	579.4	357.8	113.9	423.1	211.6
Mean	21.05	70.65	579.4	357.8	113.9	423.1	211.6
3rd Qu.	21.05	70.65	579.4	357.8	113.9	423.1	211.6
Max.	21.05	70.65	579.4	357.8	113.9	423.1	211.6

```

Encapulating bounding box...
  min  max
x 13.5 30.5
y 42.5 54.0

```

```
R> plot(izgPRS)
```

9 Example: The “perpendicularDistanceIZ” Class

Here we present an example for the perpendicular distance sampling method (Williams and Gove 2003, Williams et al. 2005, Ducey et al. 2008), this example happens to be for volume estimation. Please note that, because we know the log’s true volume from simulation, we can in fact estimate all the other attributes for the log. Normally, however, we do not know the true volume from field measurements, so we would only be able to estimate volume under “canonical” PDS, and would use the “omnibus” variant PDS given in the next section to estimate these other quantities...

```

R> pdsmet = perpendicularDistance(kpds=50, units='metric')
R> iz.pdsv = perpendicularDistanceIZ(dlogs@logs$log.1, pdsmet)
R> (izgPDS = izGrid(iz.pdsv, btr))

```

```
Object of class: InclusionZoneGrid
```

```
-----
perpendicularDistanceIZ inclusion zone grid object
-----
```

```

InclusionZone class: perpendicularDistanceIZ
  units of measurement:  metric

```

```

Grid class: RasterLayer
Number of grid cells = 361
Cell dimensions: (nrows=19, ncol=19)

```

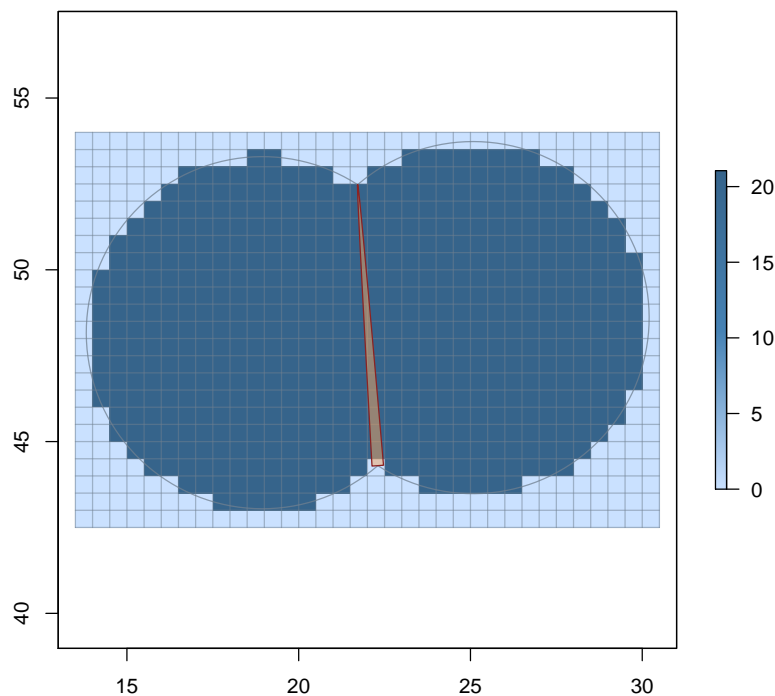


Figure 8: An “InclusionZoneGrid” object based on a “pointRelascopeIZ” object showing that the stem and inclusion zone are covered by the bounding grid.

Grid cell values**...

```
gridValues Freq
1          0 120
2         <NA> 241
```

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	100	335.6	2752	1700	541	2010	1005
1st Qu.	100	335.6	2752	1700	541	2010	1005
Median	100	335.6	2752	1700	541	2010	1005
Mean	100	335.6	2752	1700	541	2010	1005
3rd Qu.	100	335.6	2752	1700	541	2010	1005
Max.	100	335.6	2752	1700	541	2010	1005

```
Encapulating bounding box...
  min max
x 17.5  27
y 43.5  53
```

```
R> plot(izgPDS)
```

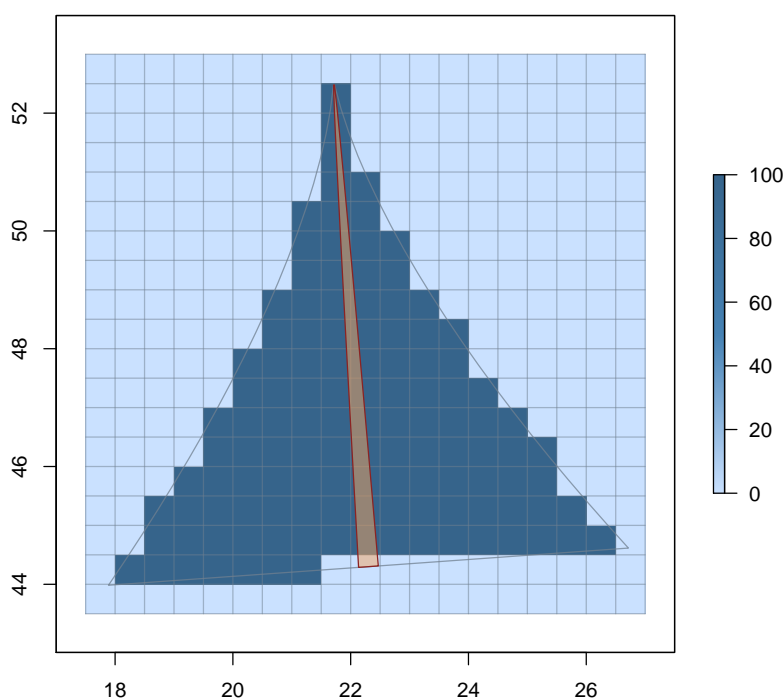


Figure 9: An “InclusionZoneGrid” object based on a “perpendicularDistanceIZ” object showing that the stem and inclusion zone are covered by the bounding grid.

As noted in *The InclusionZone Class* vignette, the inclusion zone for PDS is developed directly from the dataframe in the `taper` slot of the “downLog” object. It can be seen here that if that taper approximation is poor because it uses too few points, it has the potential to exclude grid cells that would otherwise normally be included. This in turn could lead to unexpected “simulation bias” in the sampling surface result (the same thing can happen from using too large a grid cell). Thus, it is fairly important to use a good number of log sections in the taper dataframe to avoid this possibility.

10 Example: The “omnibusPDSIZ” Class

An extension to “canonical” PDS presented in the previous section and given by Ducey et al. (2008), allows one to estimate any attribute on the log and is sometimes referred to as “omnibus” PDS. Because this method uses stem measurements perpendicular to the sample point to form the estimates, it has varying height surface in each case, with the exception of the variable we use for the PPS selection of the log¹...

```
R> iz.opds = omnibusPDSIZ(dlogs@logs$log.1, pdsmet)
R> (izgOPDS = izGrid(iz.opds, btr))
```

```
Object of class: InclusionZoneGrid
```

```
-----
omnibusPDSIZ inclusion zone grid object
-----
```

```
InclusionZone class: omnibusPDSIZ
  units of measurement: metric
```

```
Grid class: RasterLayer
Number of grid cells = 361
Cell dimensions: (nrows=19, ncol=19)
Grid cell values**...
```

```
  gridValues Freq
1           0  120
2        <NA>  241
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	100	138.4	1135	1194	380.2	2010	1005
1st Qu.	100	164.8	1351	1303	414.7	2010	1005
Median	100	209.1	1714	1468	467.2	2010	1005
Mean	100	419.2	3437	1771	563.8	2010	1005
3rd Qu.	100	314.6	2580	1801	573.2	2010	1005
Max.	100	11859.0	97243	11054	3518.7	2010	1005

```
Encapulating bounding box...
```

¹Note that if log selection is with PP to volume, then since both biomass and carbon are simply scaled versions of volume, their surfaces will also be constant.

```

      min max
x 17.5  27
y 43.5  53

```

```
R> plot(izgOPDS, estimate='coverageArea')
```

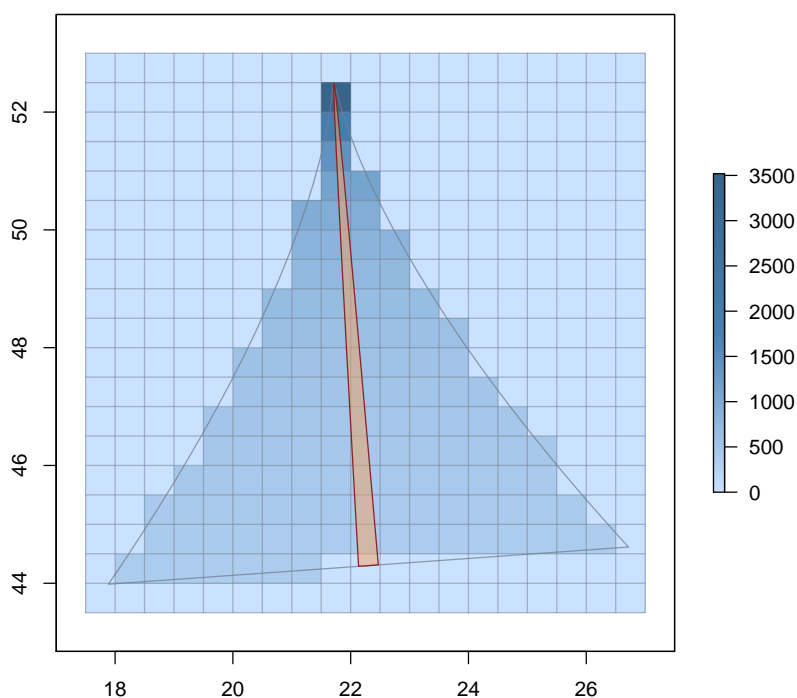


Figure 10: An “InclusionZoneGrid” object based on a “omnibusPDSIZ” object showing the variable height sampling surface for coverage area.

11 Example: The “distanceLimitedIZ” Class

Here we interject a method that is not a PDS variant, but we introduce it now because it is used in the distance limited PDS method presented below. There are two protocols for distance limited sampling: (i) a standard/canonical (DLS) with constant surface heights for all attributes, and (ii) a crude Monte Carlo based protocol (DLMCS) with varying surface height for most, but not

all attributes. The first protocol is discussed here, while DLMCS is discussed in the next section. The protocols are discussed in detail in Gove et al. (2012). The inclusion zone is covered in *The “InclusionZone” Class* vignette.

```
R> dlsMet = distanceLimited(3, units='metric')
R> iz.dls = distanceLimitedIZ(dlogs@logs$log.1, dls=dlsMet)
R> (izgDLS = izGrid(iz.dls, btr))
```

Object of class: InclusionZoneGrid

distanceLimitedIZ inclusion zone grid object

InclusionZone class: distanceLimitedIZ
units of measurement: metric

Grid class: RasterLayer

Number of grid cells = 304

Cell dimensions: (nrows=19, ncol=16)

Grid cell values**...

	gridValues	Freq
1	0	196
2	<NA>	108

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	60.56	203.2	1667	1029	327.6	1217	608.6
1st Qu.	60.56	203.2	1667	1029	327.6	1217	608.6
Median	60.56	203.2	1667	1029	327.6	1217	608.6
Mean	60.56	203.2	1667	1029	327.6	1217	608.6
3rd Qu.	60.56	203.2	1667	1029	327.6	1217	608.6
Max.	60.56	203.2	1667	1029	327.6	1217	608.6

Encapulating bounding box...

	min	max
x	18.0	26
y	43.5	53

```
R> plot(izgDLS, estimate='biomass')
```

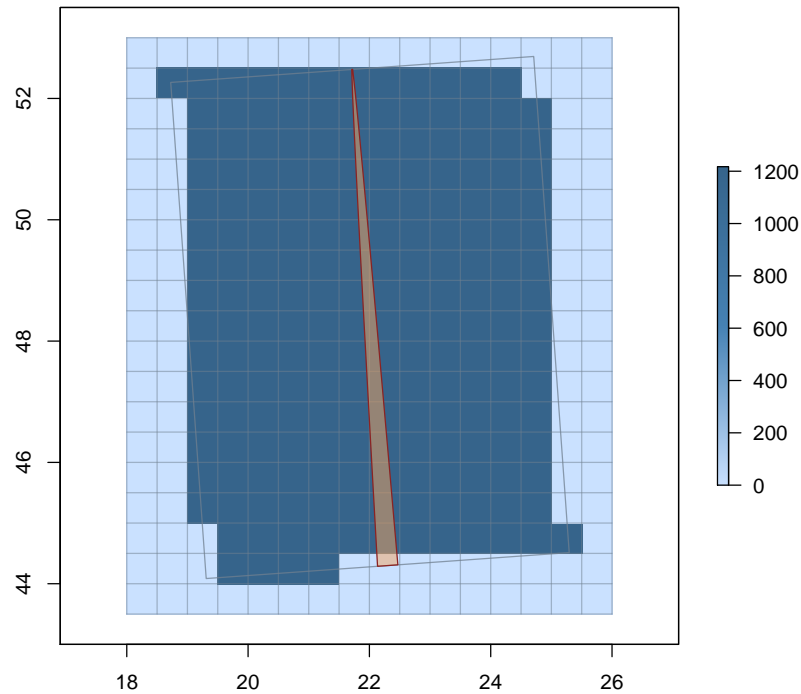


Figure 11: An “InclusionZoneGrid” object based on a “distanceLimitedIZ” object showing the variable height sampling surface for biomass.

The surfaces for log length and log density will be exactly the same under this protocol as the Monte Carlo variant as can be verified with the results in the following section. All other attribute surfaces will differ between the two protocols, as is illustrated for biomass in Figure 11.

12 Example: The “distanceLimitedMCIZ” Class

The Monte Carlo protocol for distance limited sampling is illustrated here. The inclusion zone is covered in *The “InclusionZone” Class* vignette, and the surface will be constant only for log length and density and be exactly the same as for DLS. An example follows...

```
R> dlsMet = distanceLimited(3, units='metric')
R> iz.dlmcs = distanceLimitedMCIZ(dlogs@logs$log.1, dls=dlsMet)
```



```
R> (izgDLMCS = izGrid(iz.dlmcs, btr))
```

```
Object of class: InclusionZoneGrid
```

```
-----
distanceLimitedMCIZ inclusion zone grid object
-----
```

```
InclusionZone class: distanceLimitedMCIZ
```

```
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 304
```

```
Cell dimensions: (nrows=19, ncol=16)
```

```
Grid cell values**...
```

```
gridValues Freq
```

```
1          0  196
```

```
2         <NA> 108
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	0.4405	203.2	1667	96.06	30.57	8.855	4.427
1st Qu.	21.0560	203.2	1667	664.06	211.38	423.220	211.610
Median	54.0920	203.2	1667	1064.40	338.80	1087.200	543.620
Mean	60.0290	203.2	1667	1024.00	325.94	1206.600	603.290
3rd Qu.	96.2100	203.2	1667	1419.50	451.84	1933.800	966.910
Max.	146.8300	203.2	1667	1753.60	558.20	2951.300	1475.700

```
Encapulating bounding box...
```

```
min max
```

```
x 18.0 26
```

```
y 43.5 53
```

```
R> plot(izgDLMCS, estimate='biomass')
```

Note from the summary output that the surface is indeed variable for all attributes other than density and Length. This is illustrated for biomass in Figure 12.

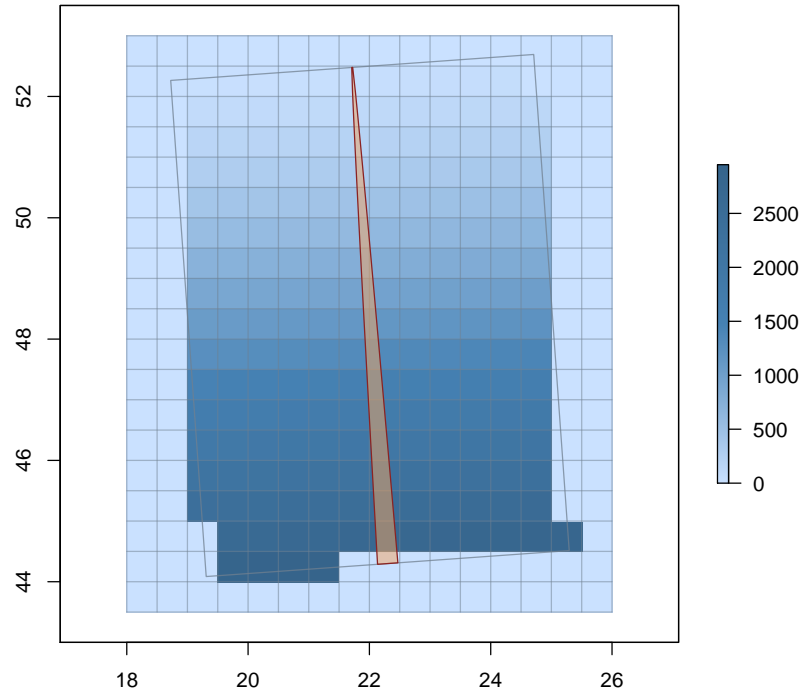


Figure 12: An “InclusionZoneGrid” object based on a “distanceLimitedMCIZ” object showing the variable height sampling surface for biomass.

13 Example: The “distanceLimitedPDSIZ” Class

This class, as explained in *The “InclusionZone” Class* vignette, is a sampling method that restricts the maximum width of the PDS inclusion zone, effectively truncating the search distance for logs. The composite effect comes from the fact that the inclusion zone can have one of three variations: (i) the inclusion zone is all PDS, (ii) the inclusion zone is all DLS, or (iii) it is a combination of the two. This flexibility can make things a bit messy, however. We again define several different protocols within this method. First, “canonical” DLPDS uses DLS for the truncated portion of the inclusion zone and canonical PDS for the section that is treated as a normal PDS sample.² In the second protocol, we substitute omnibus PDS for any section that is to be sampled with PDS, while DLMCS is used for the distance limited portion, and refer to this as “omnibus” DLPDS. Note that the difference is entirely based on the protocols for both the PDS and distance limited components

²Of course, in field applications, this method is limited to sampling only for the PPS selection variable in the PDS component for the same reasons as described above.

(if any) for each log. Both components of the inclusion zone can, therefore, be either constant or variable depending on the PPS selection strategy (volume, surface area or coverage area) and the particular attribute we are estimating (refer to the last few sections for more information). Finally, there is a “hybrid” protocol, which uses canonical PDS and DLMCS, and was the original distance limited method introduced by [Ducey et al. \(2013\)](#). Again, this method is useful only for the design attribute in field application and is design-unbiased. The sampling surface will be flat for the PDS component, but can be either flat or sloping for the DLMCS component. Details on each of the three methods can be found in [Gove et al. \(2013\)](#).

```
R> iz.dlpds = distanceLimitedPDSIZ(dlogs@logs$log.1, pds=pdsmet, dls=dlsMet)
R> (izgDLPDS = izGrid(iz.dlpds, btr))
```

Object of class: InclusionZoneGrid

a distance limited PDSIZ inclusion zone grid object

InclusionZone class: distanceLimitedPDSIZ
units of measurement: metric

Grid class: RasterLayer

Number of grid cells = 285

Cell dimensions: (nrows=19, ncol=15)

Grid cell values**...

gridValues Freq

1 0 108

2 <NA> 177

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	100.0	319.9	1667	1604	510.6	2010	1005
1st Qu.	100.0	319.9	1667	1604	510.6	2010	1005
Median	100.0	319.9	4020	2059	655.2	2010	1005
Mean	109.7	367.7	3039	1869	594.9	2205	1102
3rd Qu.	123.3	434.5	4020	2059	655.2	2477	1239
Max.	123.3	434.5	4020	2059	655.2	2477	1239

Encapulating bounding box...

	min	max
x	18.5	26
y	43.5	53

```
R> plot(izgDLPDS, estimate='biomass', showPDSPart=TRUE)
```

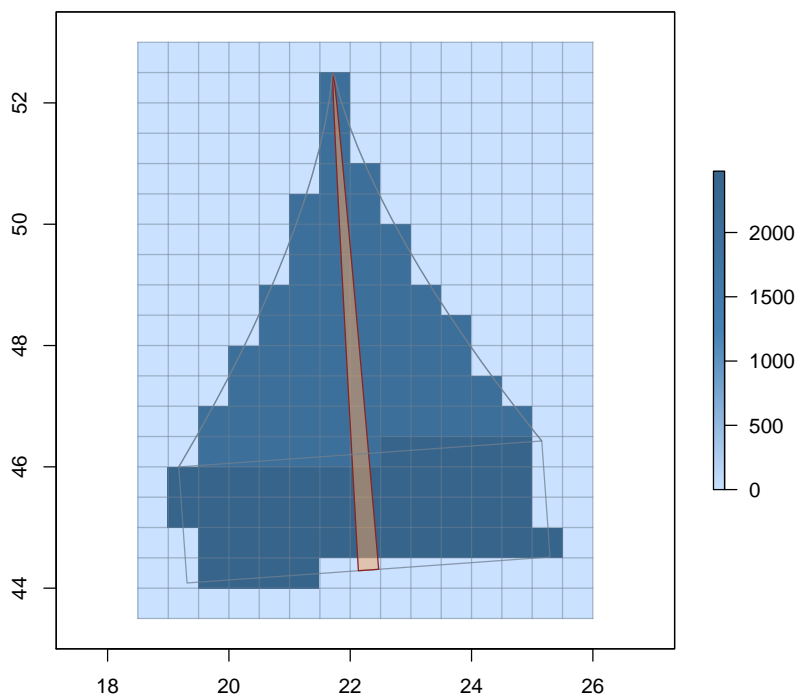


Figure 13: An “InclusionZoneGrid” object based on a “distanceLimitedPDSIZ” object showing the variable “stair step” height sampling surface for biomass.

Figure 13 shows³ the two inclusion zones in the hybrid region. Since biomass is a scaled version of volume (the PPS selection variable), the PDS component surface is constant as in Figure 9. The DLS component is also constant, just as the surface generated in Figure 11. Now we are able to see why this is a hybrid scheme more clearly. Note from the object summary that the combination of the two types of inclusion zone objects makes all of the attributes variable in case (iii), since both PDS and DLS will always produce constant height surfaces that will, in general, not be the same height, resulting in the entire surface resembling a “step” function.

³The log is randomly generated with each run of this document, and so differs with each creation, but the parameters are chosen such that it should show the two zones of case (iii).

14 Example: The “omnibusDLPDSIZ” Class

Omnibus DLPDS is a Monte Carlo-based method. Again, this is similar to canonical DLPDS with the exception that omnibus PDS is employed within the PDS component of the inclusion zone, and DLMCS is used in the distance limited portion, if any. This method will be more appropriate for most field applications since one is able to estimate any attribute shown in [Ducey et al. \(2008\)](#). The resulting surface will be variable as described in the sections for the individual component methods above.

```
R> iz.odlpds = omnibusDLPDSIZ(dlogs@logs$log.1, pds=pdsmet, dls=dlsMet)
R> (izgODLPDS = izGrid(iz.odlpds, btr))
```

Object of class: InclusionZoneGrid

a distance limited PDSIZ inclusion zone grid object

InclusionZone class: omnibusDLPDSIZ
units of measurement: metric

Grid class: RasterLayer
Number of grid cells = 285
Cell dimensions: (nrows=19, ncol=15)
Grid cell values**...

```
  gridValues Freq
1           0  108
2        <NA>  177
```

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	100.0	133.6	1667	1448	460.9	2010	1005
1st Qu.	100.0	193.5	1667	1547	492.3	2010	1005
Median	100.0	434.3	1852	1663	529.4	2010	1005
Mean	109.5	431.8	3846	1950	620.6	2201	1100
3rd Qu.	118.1	434.5	2858	1895	603.2	2374	1187
Max.	146.8	8162.1	102550	11352	3613.4	2951	1476

Encapulating bounding box...
min max
x 18.5 26

y 43.5 53

```
R> plot(izgODLPDS, estimate='surfaceArea', showPDSPart=TRUE)
```

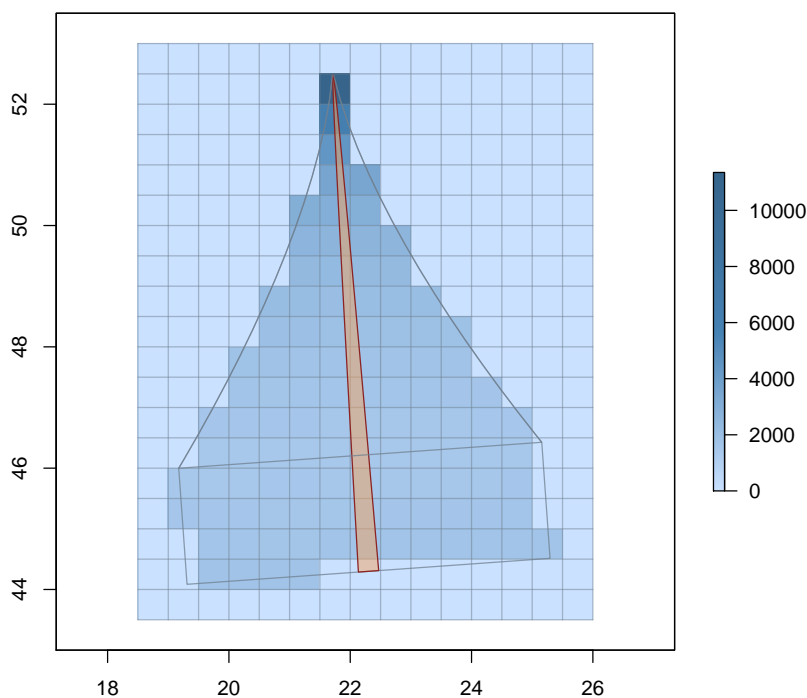


Figure 14: An “InclusionZoneGrid” object based on a “omnibusDLPDSIZ” object showing the variable height sampling surface for surface area.

It may be difficult to see in Figure 14, but the surface is actually slightly convex from butt to tip, because it varies in the reverse sense for each of the two components; i.e., larger near the butt for DLMCS, but larger near the tip for omnibus PDS.

15 Example: The “hybridDLPDSIZ” Class

Hybrid DLPDS is similar to canonical DLPDS with the exception that DLMCS is employed within the DLS component of the inclusion zone, if any. This is the original DLPDS method introduced

by Ducey et al. (2013). The resulting surface will be flat or variable depending on the attribute, as described in the sections for the individual component methods above.

```
R> iz.hdlpds = hybridDLPDSIZ(dlogs@logs$log.1, pds=pdsmet, dls=dlsMet)
R> (izgHDLPDS = izGrid(iz.hdlpds, btr))
```

```
Object of class: InclusionZoneGrid
```

```
-----
a distance limited PDSIZ inclusion zone grid object
-----
```

```
InclusionZone class: hybridDLPDSIZ
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 285
```

```
Cell dimensions: (nrows=19, ncol=15)
```

```
Grid cell values**...
```

```
gridValues Freq
```

```
1          0  108
```

```
2         <NA> 177
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

	volume	Density	Length	surfaceArea	coverageArea	biomass	carbon
Min.	100.0	319.9	1667	1448	460.9	2010	1005
1st Qu.	100.0	319.9	1667	1628	518.1	2010	1005
Median	100.0	319.9	4020	2059	655.2	2010	1005
Mean	109.5	367.7	3039	1868	594.5	2201	1100
3rd Qu.	118.1	434.5	4020	2059	655.2	2374	1187
Max.	146.8	434.5	4020	2059	655.2	2951	1476

```
Encapulating bounding box...
```

```
min max
```

```
x 18.5 26
```

```
y 43.5 53
```

```
R> plot(izgHDLPDS, estimate='surfaceArea', showPDSPart=TRUE)
```

Again, it may be difficult to tell from Figure 15, but the surface slopes downward from the butt of the log to the transition point in the DLMCS section of the inclusion zone, and is constant in the

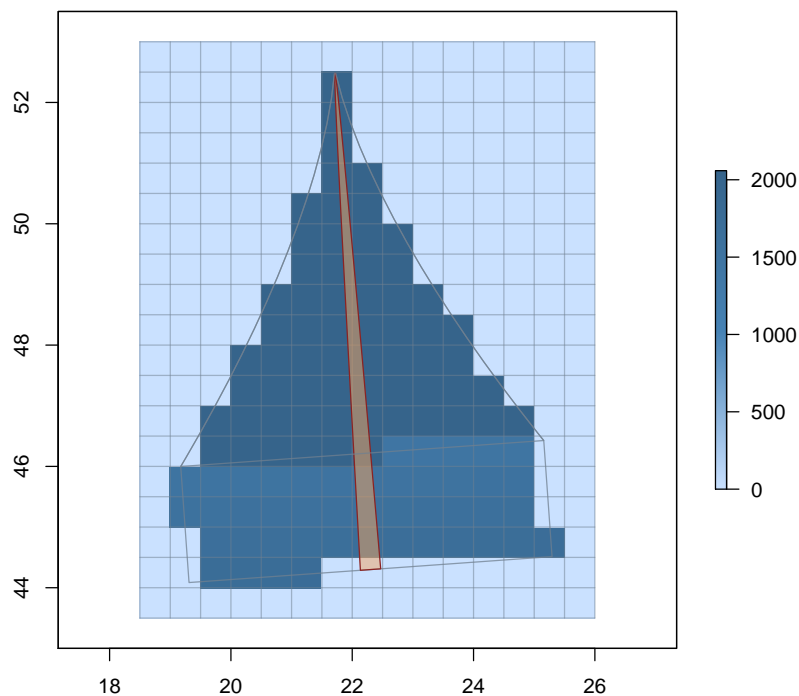


Figure 15: An “InclusionZoneGrid” object based on a “hybridDLPDSIZ” object showing the composite height sampling surface for surface area when sampling with PP volume.

PDS section.

16 Example: The “circularPlotIZ” Class

This example is for standing trees, and the example shows how the classic fixed-area circular plot method works for the “InclusionZoneGrid” class.

```
R> sttr = standingTrees(1, btr, dbh = c(10,20), topDiams=c(0,0),
+                       solidType=c(1.5,3))
R> cpiz = circularPlotIZ(sttr@trees$tree.1, plotRadius=4)
R> (cpIZG = izGrid(cpiz, btr))
```



```
Object of class: InclusionZoneGrid
```

```
-----
circularPlotIZ inclusion zone grid object
-----
```

```
InclusionZone class: circularPlotIZ
```

```
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 324
```

```
Cell dimensions: (nrows=18, ncol=18)
```

```
Grid cell values**...
```

```
gridValues Freq
```

```
1          0  202
```

```
2         <NA> 122
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

	volume	Density	basalArea	surfaceArea
Min.	14.79	198.9	3.409	496.9
1st Qu.	14.79	198.9	3.409	496.9
Median	14.79	198.9	3.409	496.9
Mean	14.79	198.9	3.409	496.9
3rd Qu.	14.79	198.9	3.409	496.9
Max.	14.79	198.9	3.409	496.9

```
--Note: either biomass or carbon (or both) had all NAs because no conversion
factor was supplied, these columns have been deleted above.
```

```
Encapulating bounding box...
```

```
min max
```

```
x 18.5 27.5
```

```
y 16.5 25.5
```

```
R> plot(cpIZG, estimate='surfaceArea')
```

17 Example: The “horizontalPointIZ” Class

This section presents an example based on horizontal point sampling for a standing tree. Note that it is very similar to the previous example for sampling with fixed-area circular plots and indeed uses the same methods thanks to class inheritance.

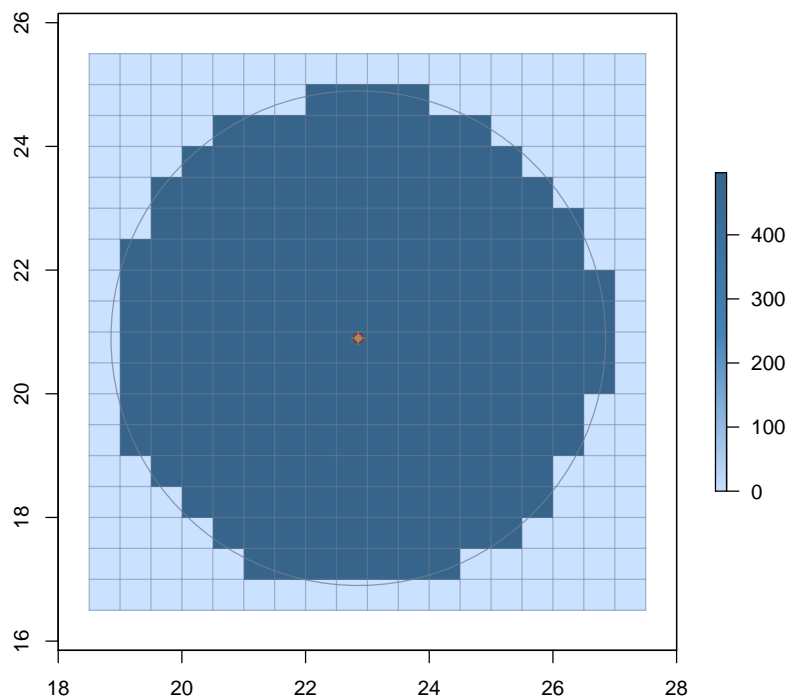


Figure 16: An “InclusionZoneGrid” object based on a “circularPlotIZ” object.

```
R> aGauge = angleGauge(baf=3) #metric
R> hpiz = horizontalPointIZ(sttr@trees$tree.1, angleGauge=aGauge)
R> (hpsIZG = izGrid(hpiz, btr))
```

Object of class: InclusionZoneGrid

circularPlotIZ inclusion zone grid object

InclusionZone class: horizontalPointIZ
units of measurement: metric

Grid class: RasterLayer
Number of grid cells = 361
Cell dimensions: (nrows=19, ncol=19)

Grid cell values**...

```
gridValues Freq
1          0  229
2         <NA> 132
```

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

	volume	Density	basalArea	surfaceArea
Min.	13.02	175.1	3	437.4
1st Qu.	13.02	175.1	3	437.4
Median	13.02	175.1	3	437.4
Mean	13.02	175.1	3	437.4
3rd Qu.	13.02	175.1	3	437.4
Max.	13.02	175.1	3	437.4

--Note: either biomass or carbon (or both) had all NAs because no conversion factor was supplied, these columns have been deleted above.

Encapulating bounding box...

```
min max
x  18 27.5
y  16 25.5
```

```
R> plot(hpsIZG, estimate='basalArea')
```

18 Example: The “horizontalLineIZ” Class

This section presents an example based on horizontal line sampling for a standing tree.

```
R> aGauge = angleGauge(baf=5) #metric
R> hliz = horizontalLineIZ(sttr@trees$tree.1, angleGauge=aGauge, lineLength = 20,
+                               orientation = 35)
R> (hlsIZG = izGrid(hliz, btr))
```

Object of class: InclusionZoneGrid

```
-----
horizontalLineIZ inclusion zone grid object
-----
```

InclusionZone class: horizontalLineIZ

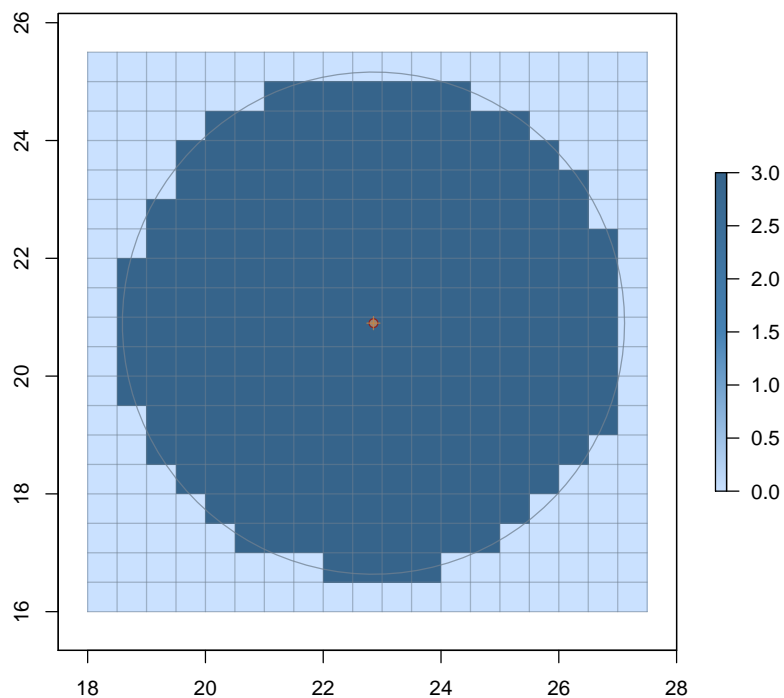


Figure 17: An “InclusionZoneGrid” object based on a “horizontalPointIZ” object.

```
units of measurement:  metric

Grid class: RasterLayer
Number of grid cells = 1512
Cell dimensions: (nrows=42, ncol=36)
Grid cell values**...
  gridValues Freq
1          0  527
2         <NA>  985
**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...
      volume Density basalArea surfaceArea
Min.    5.629   75.7    1.297    189.1
1st Qu.  5.629   75.7    1.297    189.1
Median   5.629   75.7    1.297    189.1
```

```
Mean      5.629    75.7     1.297     189.1
3rd Qu.   5.629    75.7     1.297     189.1
Max.      5.629    75.7     1.297     189.1
```

--Note: either biomass or carbon (or both) had all NAs because no conversion factor was supplied, these columns have been deleted above.

Encapulating bounding box...

```
      min  max
x 14.0 32.0
y 10.5 31.5
```

```
R> plot(hlsIZG, estimate='basalArea')
```

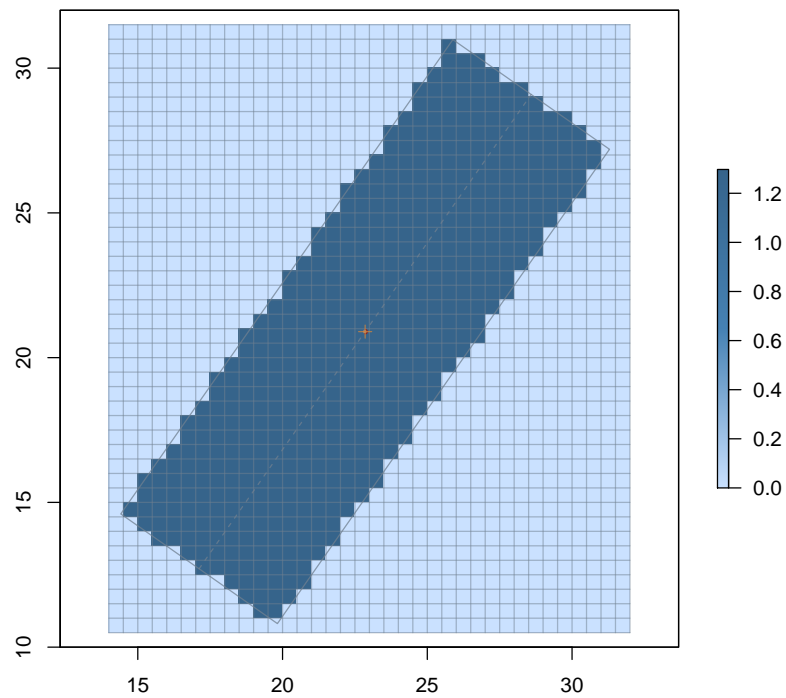


Figure 18: An “InclusionZoneGrid” object based on a “horizontalLineIZ” object.

19 Example: The “criticalHeightIZ” Class

This section presents an example based on critical height sampling (CHS) for a standing tree. Note the similarity to the “horizontalPointIZ” example; but it only is used to estimate volume...

```
R> aGauge = angleGauge(baf=3) #metric
R> chsiz = criticalHeightIZ(sttr@trees$tree.1, angleGauge=aGauge,
+                           referenceHeight='dbh')
R> (chsIZG = izGrid(chsiz, btr))
```

Object of class: InclusionZoneGrid

```
-----
criticalHeightIZ inclusion zone grid object
-----
```

InclusionZone class: criticalHeightIZ
units of measurement: metric

Grid class: RasterLayer

Number of grid cells = 361

Cell dimensions: (nrows=19, ncol=19)

Grid cell values**...

gridValues Freq

1 0 229

2 <NA> 132

**Note: data slot values get swapped with zero-valued grid cells as necessary.

Per unit area estimates in the data slot (for cells inside IZ only)...

 volume

Min. 4.135

1st Qu. 7.748

Median 11.825

Mean 12.383

3rd Qu. 16.516

Max. 23.998

--Note: either biomass or carbon (or both) had all NAs because no conversion factor was supplied, these columns have been deleted above.
Other columns with all NAs have also been removed.

Encapulating bounding box...

```
min max
x 18 27.5
```

```
y 16 25.5
```

```
R> plot(chsIZG)
```

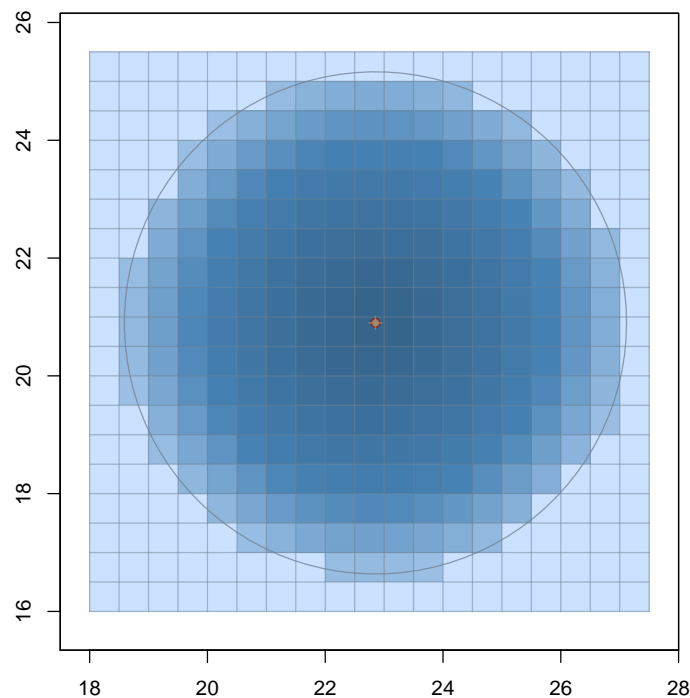


Figure 19: An “InclusionZoneGrid” object based on a “criticalHeightIZ” object.

As with a number of the other sampling methods discussed, CHS generates a variable-height surface within the inclusion zone. This is the first sampling method for standing trees that we have encountered that has this property.

20 Example: The “importanceCHSIZ” Class

Importance sampling can be coupled with CHS, producing an improved estimator (Lynch and Gove, 2013). Note in the results below the differences in the surface between importance critical height sampling (ICHS) and CHS for volume...

```
R> ichsiz = importanceCHSIZ(sttr@trees$tree.1, angleGauge=aGauge,
+                           referenceHeight='dbh')
R> (ichsIZG = izGrid(ichsiz, btr))
```

```
Object of class: InclusionZoneGrid
```

```
-----
importanceCHSIZ-based inclusion zone grid object
-----
```

```
InclusionZone class: importanceCHSIZ
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 361
```

```
Cell dimensions: (nrows=19, ncol=19)
```

```
Grid cell values**...
```

```
gridValues Freq
```

```
1          0  229
```

```
2         <NA> 132
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

```
volume
```

```
Min.      11.20
```

```
1st Qu.   12.15
```

```
Median    12.93
```

```
Mean      13.02
```

```
3rd Qu.   13.80
```

```
Max.      15.36
```

```
--Note: either biomass or carbon (or both) had all NAs because no conversion
factor was supplied, these columns have been deleted above.
```

```
Other columns with all NAs have also been removed.
```

```
Encapulating bounding box...
```

```
min max
```

```
x  18 27.5
```

```
y  16 25.5
```

```
R> plot(ichsIZG)
```

If you view the surface in Figure 20 using `plot3D` (§ 23), you will see the slight unevenness that is reported in the summary for the object above—it is not completely flat even though it appears

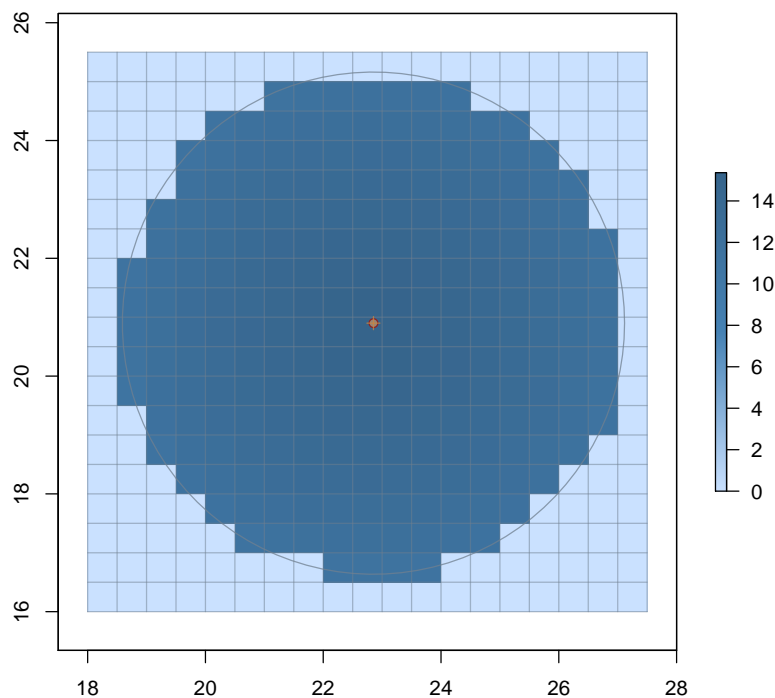


Figure 20: An “InclusionZoneGrid” object based on a “importanceCHSIZ” object.

so in Figure 20. However, it is much closer to level than CHS, and hence a more efficient method variance-wise.

21 Example: The “antitheticICHSIZ” Class

An antithetic variant to ICHS moves the sampling point on the bole to facilitate measurement (Lynch and Gove, 2013). Again note in the results below the differences in the surface between antithetic importance critical height sampling (AICHS), ICHS, and CHS for volume...

```
R> aichsiz = antitheticICHSIZ(sttr@trees$tree.1, angleGauge=aGauge,
+                             referenceHeight='dbh')
R> (aichsIZG = izGrid(aichsiz, btr))
```

```
Object of class: InclusionZoneGrid
```

```
-----
importanceCHSIZ-based inclusion zone grid object
-----
```

```
InclusionZone class: antitheticICHSIZ
```

```
units of measurement: metric
```

```
Grid class: RasterLayer
```

```
Number of grid cells = 361
```

```
Cell dimensions: (nrows=19, ncol=19)
```

```
Grid cell values**...
```

```
gridValues Freq
```

```
1          0  229
```

```
2         <NA> 132
```

```
**Note: data slot values get swapped with zero-valued grid cells as necessary.
```

```
Per unit area estimates in the data slot (for cells inside IZ only)...
```

```
volume
```

```
Min.      12.46
```

```
1st Qu.   12.78
```

```
Median    12.94
```

```
Mean      13.02
```

```
3rd Qu.   13.20
```

```
Max.      14.12
```

```
--Note: either biomass or carbon (or both) had all NAs because no conversion
factor was supplied, these columns have been deleted above.
```

```
Other columns with all NAs have also been removed.
```

```
Encapulating bounding box...
```

```
min max
```

```
x  18 27.5
```

```
y  16 25.5
```

```
R> plot(aichsIZG)
```

22 Example: The “pairedAICHSIZ” Class

The last variant that is related to CHS is paired antithetic importance critical height sampling (PAICHS). It combines two measurements on the bole in the estimator (Lynch and Gove, 2013).

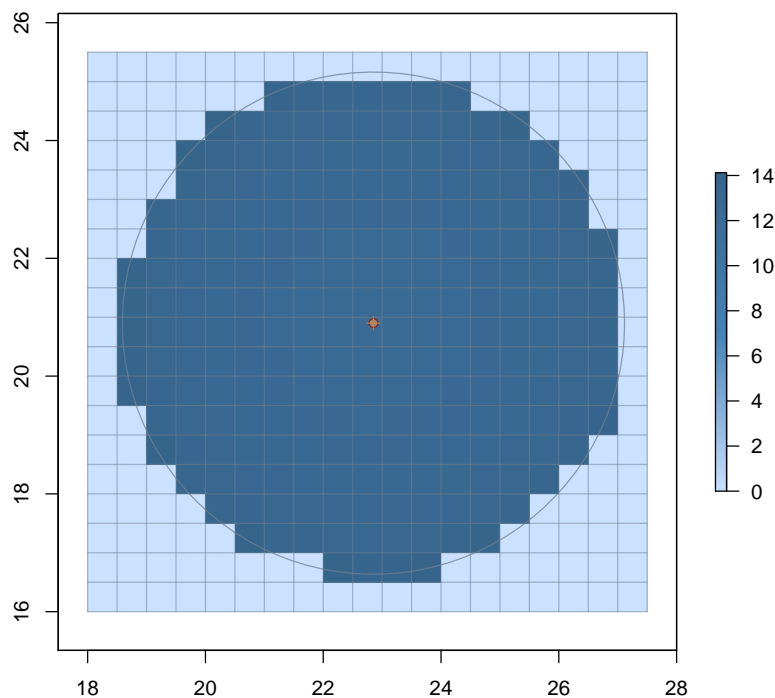


Figure 21: An “InclusionZoneGrid” object based on a “antitheticICHSIZ” object.

Again note in the results below the differences in the surface between PAICHS, AICHS, ICHS, and CHS for volume...

```
R> paichsiz = pairedAICHSIZ(sttr@trees$tree.1, angleGauge=aGauge,
+                           referenceHeight='dbh')
R> (paichsIZG = izGrid(paichsiz, btr))
```

Object of class: InclusionZoneGrid

importanceCHSIZ-based inclusion zone grid object

InclusionZone class: pairedAICHSIZ
units of measurement: metric

```

Grid class: RasterLayer
Number of grid cells = 361
Cell dimensions: (nrows=19, ncol=19)
Grid cell values**...
  gridValues Freq
1          0  229
2         <NA> 132
**Note: data slot values get swapped with zero-valued grid cells as necessary.

```

Per unit area estimates in the data slot (for cells inside IZ only)...

```

      volume
Min.      12.32
1st Qu.   12.67
Median    13.21
Mean      13.02
3rd Qu.   13.30
Max.      13.57

```

```

--Note: either biomass or carbon (or both) had all NAs because no conversion
       factor was supplied, these columns have been deleted above.
       Other columns with all NAs have also been removed.

```

```

Encapulating bounding box...
  min  max
x  18 27.5
y  16 25.5

```

```
R> plot(paichsIZG)
```

23 Using *plot3D*

The *plot3D* generic was extended to handle objects of class “InclusionZoneGrid”. Its use is simple, just remember to use the *estimate* argument to specify the desired surface attribute to be rendered...

```
R> plot3D(izgODLPDS, estimate='surfaceArea')
```

Please be aware that the *plot3D* method adjusts the *x* and *y* axes by default to scale the image for presentation. This scaling is very helpful for viewing, but tends to distort the two axes relative to the height of the surface. To view the true units and hence see what the surface looks like without any scaling, use the *adjust=FALSE* argument to display the surface in *plot3D*.

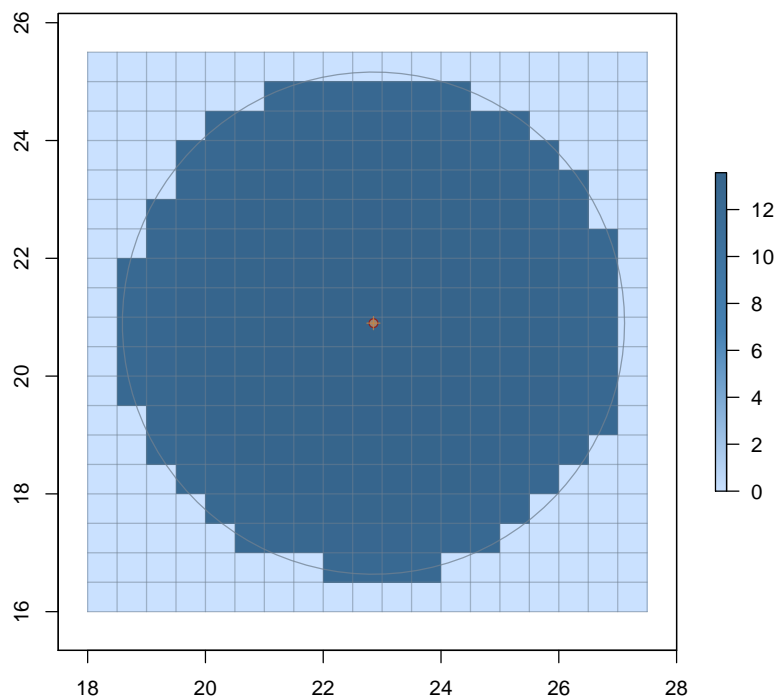


Figure 22: An “InclusionZoneGrid” object based on a “pairedAICHSIZ” object.

References

- M. J. Ducey, M. S. Williams, J. H. Gove, and H. T. Valentine. Simultaneous unbiased estimates of multiple downed wood attributes in perpendicular distance sampling. *Canadian Journal of Forest Research*, 38:2044–2051, 2008. 18, 21, 29
- M. J. Ducey, M. S. Williams, J. H. Gove, S. Roberge, and R. S. Kenning. Distance limited perpendicular distance sampling for coarse woody material: Theory and field results. *Forestry*, 86: 119–128, 2013. 27, 31
- J. H. Gove and P. C. Van Deusen. On fixed-area plot sampling for downed coarse woody debris. *Forestry*, 84(2):109–117, 2011. 7, 12, 13
- J. H. Gove, A. Ringvall, G. Ståhl, and M. J. Ducey. Point relascope sampling of downed coarse woody debris. *Canadian Journal of Forest Research*, 29(11):1718–1726, 1999. 17

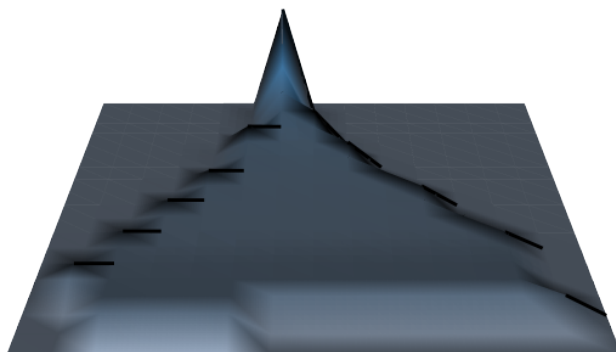


Figure 23: Representation of the sampling surface (via an “InclusionZoneGrid” object) for a single log sampled with “omnibusDLPDS”.

- J. H. Gove, M. J. Ducey, A. Ringvall, and G. Ståhl. Point relascope sampling: A new way to assess down coarse woody debris. *Journal of Forestry*, 4:4–11, 2001. 17
- J. H. Gove, M. J. Ducey, and H. T. Valentine. A distance limited method for sampling downed coarse woody debris. *Forest Ecology and Management*, 282:53–62, 2012. 23
- J. H. Gove, M. J. Ducey, H. T. Valentine, and M. S. Williams. A comprehensive comparison of the perpendicular distance method for sampling downed coarse woody debris. *Forestry*, 86:129–143, 2013. 27
- T. B. Lynch and J. H. Gove. An antithetic variate to facilitate upper-stem height measurements for critical height sampling and fixed-radius plot sampling with importance sampling. *Canadian Journal of Forest Research*, 2013. (In review). 39, 41, 42
- M. S. Williams and J. H. Gove. Perpendicular distance sampling: an alternative method for sampling downed coarse woody debris. *Canadian Journal of Forest Research*, 33:1564–1579, 2003. 18

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- M. S. Williams, M. J. Ducey, and J. H. Gove. Assessing surface area of coarse woody debris with line intersect and perpendicular distance sampling. *Canadian Journal of Forest Research*, 35: 949–960, 2005. 18