Investigation of towed hydrophone monitoring power for harbour porpoise on the SCANS II survey.

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ABSTRACT
We investigate the power of harbour porpoise monitoring programmes which use an index of relative abundance to detect change. Power depends on the variability in the constant of proportionality relating the index to absolute abundance, as well as on the variability in the index given this constant. We estimate both from the SCANS II data and from European Seabirds at Sea (ESAS) data. Estimates of the coefficient of variation of the constant of proportionality are large and this results in very low power. Because these estimates may be unrealistically large for well-designed monitoring programs, we feel it is inappropriate to draw strong conclusions about the power of future monitoring programmes based on them.

ESAS surveys are found to be more efficient in terms of effort required to achieve given power, than the SCANS II passive acoustic surveys. However, the comparison may not be a fair one, for the following reason. The estimated CV of the constant of proportionality is obtained from the ratio of the index of density and the corresponding SCANS II absolute density estimate; the ESAS index is likely to be more highly correlated with the SCANS II estimate than the acoustic index, because like the SCANS II estimate, it is based on visual detections. In addition, standardization of the passive acoustic survey methods could yield substantially higher efficiency.

We provide a table giving power as a function of the CV of the constant of proportionality and the CV of the index, given this constant - this can be used to compare methods if reliable estimates of these CVs are available.

METHODS

<u>Sources of variance</u>

Consider the situation in which we have a measure of relative abundance, *R*, which is proportional to absolute abundance, *N*, but subject to random error. In particular, suppose $E[R \mid N] = \beta N$. Suppose also that there are two sources of randomness in *R*, the first being randomness in the constant of proprtionality (β), the second being randomness in *R* conditional on β (and *N*). We write the variance of β as σ_β^2 and the variance of R conditional on β and *N* as $\sigma_{R|\beta}^2(N)$.

By way of obtaining an expression for the coefficient of variation (CV) of *R* for our power calculations, we first obtain an expression for the variance of *R* (given *N*):

$$\begin{aligned} Var[R \mid N] &= E_\beta[Var[R \mid \beta, N]] + Var_\beta[E[R \mid \beta, N]] \\ &= E_\beta[\sigma_{R|\beta}^2(N)] + Var_\beta[\beta N] \\ &= E_\beta[\sigma_{R|\beta}^2(N)] + \sigma_\beta^2 N^2 \end{aligned} \tag{1}$$

From this it follows that the squared CV of *R* is

$$CV[R \mid N]^2 = \frac{E_\beta[\sigma_{R|\beta}^2(N)]}{E_\beta[\mu_{R|\beta}(N)]^2} + CV[\beta]^2 \tag{2}$$

where $\mu_{R|\beta}(N)$ is the expected value of *R*, given β and *N*. In our context, $CV[\beta]$ will depend on the heterogeneity of things such as survey platforms, detectors and environmental conditions, but will not normally depend on survey effort. The first term on the RHS of Equation (2), on the other hand, will depend on survey effort (i.e. length of transect surveyed) – the greater the effort, the lower it will be.

To proceed further we need to make some assumption about the form of $E_{\beta}[\sigma^2_{R|\beta}(N)] / E_{\beta}[\mu_{R|\beta}(N)]^2]$. It is convenient, and not unreasonable to assume that it does not depend on *N*. We assume that $CV[R \mid \beta]^2 = \sigma^2_{R|\beta}(N)/\{\mu_{R|\beta}(N)\}^2$ is the same for all *N*.

<u>Dealing with randomness in N</u>
The above calculations apply in the case of regression of *R* on *N*. But, we do not observe *N*. We only have estimates of it, and these are random variables. Some component of the estimates of the variance of β and $\sigma^2_{R|\beta}(N)$ obtained from the data is due to the variance of the estimator of *N*.

To estimate σ^2_{β}, we note that $Var[\hat{\beta}] = E_{\beta}[Var[\hat{\beta} \mid \beta]] + Var_{\beta}[E[\hat{\beta} \mid \beta]] = \sigma^2_{\beta} + Var_{\beta}[E[\hat{\beta} \mid \beta]]$, where $\hat{\beta}$ is estimated taking account of variance in $\hat{N}$ and R. It follows that $\sigma^2_{\beta} = Var[\hat{\beta}] - Var_{\beta}[E[\hat{\beta} \mid \beta]]$. We can estimate $Var[\hat{\beta}]$ and $Var_{\beta}[E[\hat{\beta} \mid \beta]]$ from the survey data. The former is estimated using the inter-vessel variance in estimated β; the latter is estimated using the estimates of $CV[\hat{D}_{vessel}]$ and $CV[R_{vessel}]$ obtained from survey data. Details are given separately for the acoustic and ESAS data in the sections covering each below.

<u>Power calculations</u>
We consider scenarios in which a series of 10 annual surveys and we are interested in the power to detect a 5% per annum exponential decline in abundance over this period, using a 5% significance level.

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We frame our power calculations in terms of effort required to achieve given power. We use the programme Trends[1] (Gerodette and Brandon, 2003) for power calculation. This provides an estimate of the total CV ($CV[R]$) required for given power; we refer to this as the target *CV* of *R* and denote it $CV_T[R]$. In order to convert this target *CV* into target efffort (i.e. the effort required to achieve given power), we need an expression for effort as a function of $CV_T[R]$. We obtain this below.

Assuming that $CV[R \mid \beta]^2$ is inversely proportional to effort, we use Equation (7.5) of Buckland *et al.* (2001), together with an estimate of $CV_0[R \mid \beta]^2$ obtained from a survey with effort L_0, to get the following formula for the line length required to achieve a target $CV[R \mid \beta]$, which we denote $CV_T[R \mid \beta]$:

$$L = \frac{L_0 \times CV_0[R \mid \beta]^2}{CV_T[R \mid \beta]^2} \qquad (3)$$

Because programme Trends outputs $CV_T[R]$ rather than $CV_T[R \mid \beta]$, we need to express $CV_T[R \mid \beta]$ in terms of $CV_T[R]$ in order to use Equation (3) with the programme. From Equation (2), and approximating $E_{\beta}[\sigma^2_{R|\beta}(N)] / E_{\beta}[\mu_{R|\beta}(N)]^2]$ by $CV[R \mid \beta]^2$, we have that

[1] Assuming CV independent of *N* and a two-tailed test.

$CV_T[R \mid \beta]^2$ is approximately equal to $CV_T[R]^2 - CV[\beta]^2$. Substititing into Equation (3) get we see that for any given $CV[\beta]$, the effort required to achieve the required power is approximately

$$L = \frac{L_0 \times CV_0[R \mid \beta]^2}{CV_T[R]^2 - CV[\beta]^2} \tag{4}$$

The higher $CV[\beta]$ is, the more effort is required to achieve given power. Moreover, $CV[\beta]$ is a lower bound for $CV[R]$: even if it were possible to reduce $CV[R \mid \beta]$ to zero by using sufficient effort, this cannot reduce $CV[R]$ below $CV[\beta]$. $CV[\beta]$ can in principle be reduced by standardising survey effort (i.e. standardising things like survey platforms, detectors, and enviromental conditions in which surveys are conducted). When $CV[\beta]$ is greater than $CV[R \mid \beta]$, increasing effort in order to reduce $CV[R]$ will not be the most effective way of increasing power – it will be more effective to reduce $CV[\beta]$ by standardising survey effort.

When comparing the power associated with surveys from different kinds of survey platform (aerial vs towed passive acoustic, for example), both $CV[\beta]$ and $CV[R \mid \beta]$ associated with each platform are relevant. Unfortunately, it is very difficult to estimate $CV[\beta]$ reliably for any particular survey or platform.

In order to estimate $CV[\beta]$ from available data, we need to make some assumptions about the source of randomness. Variation in β on any monitoring programme will depend on the survey platforms, detectors and environmental conditions applying during the course of the programme. It can be minimised by controlling for as many sources of variation as possible, but it is difficult or impossible to predict what particular $CV[\beta]$ will apply. For the purposes of our calculations here, we use the $CV[\beta]$ arising from of the inter-vessel variation in β. We also consider lower levels of $CV[\beta]$.

In what follows we use what relevant data we have available to guide us but all conclusions are conditional on the values of $CV[\beta]$ and $CV_0[R \mid \beta]$ used. From Equation (4) it is apparent that given the $CV_T[R]$ required to achieve a specified power, the effort required depends on $L_0 CV_0[R \mid \beta]^2$ and $CV[\beta]$. In view of our relative ignorance of the likely values these two quantities (and $CV[\beta]$ in particular) for surveys in a future monitoring programme, we give the required effort for a range of values of $L_0 CV_0[R \mid \beta]^2$ and $CV[\beta]$ in Table 2.

Shipboard acoustic survey

We use density (*D*) rather than abundance (*N*), but the results above apply with *N* replaced by *D*.

We use the results of Burt *et al.* (2006), together with the acoustic detection rates and variances shown in Table 1, to obtain values for $CV[\beta]$ and $CV_0[R \mid \beta]^2$ to use in power calculations. Acoustic encounter rates, *R*, are obtained using data from all sea states (Beaufort 0-5), while estimates of *D* are obtained using data from effort in Beaufort 0-2 only. One consequence of this is that pairs of estimates of *D* and *R* are available only at the stratum (vessel) level, not by transect. As a result, estimates of β for each vessel must be obtained from a single pair of estimates of *D* and *R* for each vessel. That is, $\hat{\beta}_{vessel} = R_{vessel} / \hat{D}_{vessel}$. From the survey we have estimates of $CV[\hat{D}_{vessel}]$ and $CV[R_{vessel}]$. Using the Delta method, and assuming that R_{vessel} and $\hat{D}_{vessel}$ are independent, we estimate $CV[\hat{\beta}_{vessel}]$ as follows: $CV[\hat{\beta}_{vessel}] \approx \sqrt{CV^2[R_{vessel}] + CV^2[\hat{D}_{vessel}]}$ and use this as an estimate of $CV[\hat{\beta} \mid \beta]$.

Estimates of *D* and *R* for each vessel are shown in Figure 1. We used these to estimate $CV[\beta]$ and $CV_0[R \mid \beta]^2$, as detailed below.

The vessels IN, ZI and MC were excluded because they surveyed in areas of predominantly low harbour porpoise density to the west of the North Sea, and estimates of *D* have low precision as a result. Vessels IN also has a very low acoustic detection sample size (n=20). In addition, VH and ZI have acoustic bias correction factors greater than 2 and corrected acoustic encounter rate estimates are therefore considered somewhat unreliable. We consider two scenarios, one excluding IN, ZI and MC, and another excluding VH as well.

Estimation of $CV_0[R \mid \beta]^2$ from the results of Burt *et al*. (2006) is a bit problematic because of the small sample sizes per vessel and because $\sigma^2_{R|\beta}(D)$ appears to decrease with *D*, which seems implausible (and contrary to our assumption above). The decrease is caused largely by the occurrence of non-zero and sometimes quite high detection rates when estimated *D* is zero. This is likely a consequence of the fact that the *D* used by Burt *et al*. (2006) is not in fact *D* but an estimate of *D* (which may be zero even when true *D* is greater than zero). To obtain an order-of-magnitude estimate of $CV_0[R \mid \beta]^2$, we use the estimated CV of the stratified mean of the estimates across vessels. Using all vessels except IN, ZI and MC gives an estimate of $CV_0[R \mid \beta]^2$ of 16%. The total length of transect across vessels is 8,488 km. This leads to an estimate of $L_0 CV_0[R \mid \beta]^2$ of 207. Estimates for D and R for only those vessels used to estimate $CV[\beta]$ and $CV_0[R \mid \beta]^2$ are shown in Figure 2.

The CV of the estimates of β for each of the vessels participating in SCANS II is 83%. It is clear from Table 2 that even with infinite effort, the maximum power attainable in this case is less than 10%.

The SCANS II survey involved around 9,000 km of shipboard acoustic survey in sea states 5 and below. If $CV[\beta]$ could be reduced to 10%, this would give a power of just over 80%. (To see this, look in the 10% power column at entries in Table 2 for $L_0 CV_0[R \mid \beta]^2$=200, which is close to that obtained above: the required effort for 80% power is 16,000 km, which is close to that of SCANS II, while the required effort for 90% power rises to 28,986.) If $CV[\beta]$ was 15%, a power of just over 60% would be achievable, while if it rose to 20% a power of only just over 40% would be achievable. Other scenarios are presented in Table 2. With lower $L_0 CV_0[R \mid \beta]^2$, greater power is attainable for the same effort.

European Seabirds At Sea (ESAS) programme visual sightings

We use the results of Burt *et al.* (2006) to obtain values for $CV[\beta]$ and $CV_0[R \mid \beta]^2$ for power calculations, and make the same assumptions about the sources of variation in β. We also estimate $CV_0[R \mid \beta]^2$ in the same way. However, we did not use vessel VH for this scenario because although the CV of its encounter rate is not atypically large, its variance is and this, toghether with the fact that stratum VH is a high-density stratum leads to it dominating the estimate of $CV_0[R \mid \beta]^2$ (which is based on a stratified mean density). Density is again used in place of abundance. Estimates of *D* and *R* for each vessel are shown in Figure 3.

$CV[\beta]$ is estimated to be 52% and $CV_0[R \mid \beta]$ is estimated to be 21%. With a total sightings effort of 3,565 km in sea states less than 2 for the vessels used, $L_0 CV_0[R \mid \beta]^2$ is estimated to be 158. Referring to Table 2 (in the column for $CV[\beta]$=50% and rows with $L_0 CV_0[R \mid \beta]^2$ between 125 and 200) using these figures, we see that a power of 10% is achievable, but little more. If $CV[\beta]$ could be kept as low as 10%, 50% power would be achievable with effort of just over 3,500 km. If $CV[\beta]$ rose to 15%, a power of 40% would be achievable with this effort, while if it rose to 20% a power of between 3o% and 40% would be achievable.

Conclusions

For the realised effort on SCANS II and for given $CV[\beta]$, acoustics give greater power than ESAS data. Part of the reason for this is that the acoustics are able to achieve greater effort because they can survey in a wider range of sea states. If the ESAS seabird observers could achieve the same length of trackline on-effort as the acoustics, we would expect more power from ESAS data than from the passive acoustic survey data because both $CV[\beta]$ and $L_0 CV_0[R \mid \beta]$ are estimated to be lower for ESAS data than for the passive acoustics. However, there are two important caveats to this statement. These are as follows: (1) When vessel VH is included in the ESAS analysis, $L_0 CV_0[R \mid \beta]$ rises to 370, which is greater than that for the acoustic data and this leads to lower power. (2) These calculations assume that the indices of abundance and the abundance estimates from SCANS II are independent. In truth the ESAS indices are likely to be substantially more correlated with the SCANS II abundance estimates than are the acoustic indices – because both ESAS and SCANS II detections are based on visual cues (from the same vessel, at the same time).

In addition, the above analyses are based on somewhat arbitrary values for $CV[\beta]$ for future surveys. Standardisation of the passive acoustic surveys by using the same vessel, for example, could substantially increase efficiency.

Conclusions depend heavily on $CV[\beta]$ and rather than draw inferences which may be inapproriate for future monitoring surveys because of this, we refer readers to Table 2. This can provide guidance regarding power for a given monitoring programme once more reliable information on the $CV[\beta]$ and $L_0 CV_0[R \mid \beta]^2$ which apply on the particular programme are obtained.

References

Gerrodette, T and Brandon, J. 2003. TRENDS for Windows 95/98/2000/XP- Version 3.0. http://swfsc.noaa.gov/textblock.aspx?Division=PRD&ParentMenuId=228&id=4740

Table 1: Acoustic detection rate data. R is the encounter rate, *n* the number of detections, *L* the effort (in km), "*correction*" the estimated acoustic correction for vessel noise, *k* the number of transects and Var[*R*] the transect-based estimate of the variance of *R*.

Vessel	*n*	*L*	*correction*	*R*	$\hat{\beta}$	*k*	Var[*R*]
GO	84	2405.0	1.1614	0.04056	0.1380	18.00	840.92
IN	6	3342.1	1.2735	0.00229	0.1203	50.00	36.85
MC	37	2318.5	1.0000	0.01596	0.2382	34.00	124.01
SK	83	1691.1	1.5668	0.07690	0.2262	37.00	809.20
VH	30	1844.2	2.6303	0.04279	0.0761	13.00	598.24
WF	22	2547.7	1.8408	0.01590	0.0898	16.00	354.70
ZI	15	3365.3	2.6002	0.01159	0.0284	20.00	99.49

Table 2: Effort (km of transect) required to achieve given power to detect 5% decline in abundance, as a function of $CV[\beta]$ and $L_o CV_0[R \mid \beta]^2$ (see text for details). "Inf" means power is unattainable.

		$CV[\beta]$								
Power	$L_o CV_0[R \mid \beta]^2$	0%	10%	15%	20%	30%	40%	50%	60%	70%
	1	2	2	2	2	3	3	4	8	Inf
	5	10	10	11	11	13	15	21	38	Inf
	10	20	21	21	22	25	30	42	77	Inf
	20	41	42	43	44	50	61	83	154	Inf
	30	61	63	64	67	75	91	125	231	Inf
	40	82	83	86	89	100	121	167	308	Inf
10%	50	102	104	107	111	125	152	208	385	Inf
	60	122	125	128	133	150	182	250	462	Inf
	75	153	156	160	167	188	227	313	577	Inf
	100	204	208	214	222	250	303	417	769	Inf
	125	255	260	267	278	313	379	521	962	Inf
	200	408	417	428	444	500	606	833	1538	Inf
	360	735	750	770	800	900	1091	1500	2769	Inf
	1	7	7	8	10	18	Inf	Inf	Inf	Inf
	5	35	37	41	48	92	Inf	Inf	Inf	Inf
	10	69	74	82	96	184	Inf	Inf	Inf	Inf
	20	139	149	164	192	368	Inf	Inf	Inf	Inf
	30	208	223	246	287	551	Inf	Inf	Inf	Inf
	40	277	298	328	383	735	Inf	Inf	Inf	Inf
20%	50	346	372	410	479	919	Inf	Inf	Inf	Inf
	60	416	446	492	575	1103	Inf	Inf	Inf	Inf
	75	519	558	615	718	1379	Inf	Inf	Inf	Inf
	100	693	744	820	958	1838	Inf	Inf	Inf	Inf
	125	866	930	1025	1197	2298	Inf	Inf	Inf	Inf
	200	1385	1488	1641	1916	3676	Inf	Inf	Inf	Inf
	360	2493	2679	2953	3448	6618	Inf	Inf	Inf	Inf
	1	12	13	16	23	Inf	Inf	Inf	Inf	Inf
	5	59	67	81	113	Inf	Inf	Inf	Inf	Inf
	10	119	135	162	227	Inf	Inf	Inf	Inf	Inf
	20	238	270	325	454	Inf	Inf	Inf	Inf	Inf
	30	357	405	487	680	Inf	Inf	Inf	Inf	Inf
	40	476	540	649	907	Inf	Inf	Inf	Inf	Inf
30%	50	595	675	812	1134	Inf	Inf	Inf	Inf	Inf
	60	713	810	974	1361	Inf	Inf	Inf	Inf	Inf
	75	892	1012	1218	1701	Inf	Inf	Inf	Inf	Inf
	100	1189	1350	1623	2268	Inf	Inf	Inf	Inf	Inf
	125	1486	1687	2029	2834	Inf	Inf	Inf	Inf	Inf
	200	2378	2699	3247	4535	Inf	Inf	Inf	Inf	Inf
	360	4281	4858	5844	8163	Inf	Inf	Inf	Inf	Inf
	1	17	21	28	57	Inf	Inf	Inf	Inf	Inf
	5	87	105	142	284	Inf	Inf	Inf	Inf	Inf
	10	174	210	285	568	Inf	Inf	Inf	Inf	Inf
	20	347	420	570	1136	Inf	Inf	Inf	Inf	Inf
	30	521	630	855	1705	Inf	Inf	Inf	Inf	Inf
	40	694	840	1140	2273	Inf	Inf	Inf	Inf	Inf
40%	50	868	1050	1425	2841	Inf	Inf	Inf	Inf	Inf
	60	1042	1261	1709	3409	Inf	Inf	Inf	Inf	Inf
	75	1302	1576	2137	4261	Inf	Inf	Inf	Inf	Inf
	100	1736	2101	2849	5682	Inf	Inf	Inf	Inf	Inf
	125	2170	2626	3561	7102	Inf	Inf	Inf	Inf	Inf
	200	3472	4202	5698	11364	Inf	Inf	Inf	Inf	Inf
	360	6250	7563	10256	20455	Inf	Inf	Inf	Inf	Inf
	1	23	29	46	244	Inf	Inf	Inf	Inf	Inf
	5	113	147	231	1220	Inf	Inf	Inf	Inf	Inf
	10	227	293	463	2439	Inf	Inf	Inf	Inf	Inf
	20	454	587	926	4878	Inf	Inf	Inf	Inf	Inf
	30	680	880	1389	7317	Inf	Inf	Inf	Inf	Inf
	40	907	1173	1852	9756	Inf	Inf	Inf	Inf	Inf
50%	50	1134	1466	2315	12195	Inf	Inf	Inf	Inf	Inf
	60	1361	1760	2778	14634	Inf	Inf	Inf	Inf	Inf
	75	1701	2199	3472	18293	Inf	Inf	Inf	Inf	Inf
	100	2268	2933	4630	24390	Inf	Inf	Inf	Inf	Inf
	125	2834	3666	5787	30488	Inf	Inf	Inf	Inf	Inf
	200	4535	5865	9259	48780	Inf	Inf	Inf	Inf	Inf
	360	8163	10557	16667	87805	Inf	Inf	Inf	Inf	Inf

Table 2 (ctd.)

		$CV[\beta]$								
Power	$L_o CV_0[R \mid \beta]^2$	0%	10%	15%	20%	30%	40%	50%	60%	70%
60%	1	28	38	74	Inf	Inf	Inf	Inf	Inf	Inf
	5	139	192	368	Inf	Inf	Inf	Inf	Inf	Inf
	10	277	383	735	Inf	Inf	Inf	Inf	Inf	Inf
	20	554	766	1471	Inf	Inf	Inf	Inf	Inf	Inf
	30	831	1149	2206	Inf	Inf	Inf	Inf	Inf	Inf
	40	1108	1533	2941	Inf	Inf	Inf	Inf	Inf	Inf
	50	1385	1916	3676	Inf	Inf	Inf	Inf	Inf	Inf
	60	1662	2299	4412	Inf	Inf	Inf	Inf	Inf	Inf
	75	2078	2874	5515	Inf	Inf	Inf	Inf	Inf	Inf
	100	2770	3831	7353	Inf	Inf	Inf	Inf	Inf	Inf
	125	3463	4789	9191	Inf	Inf	Inf	Inf	Inf	Inf
	200	5540	7663	14706	Inf	Inf	Inf	Inf	Inf	Inf
	360	9972	13793	26471	Inf	Inf	Inf	Inf	Inf	Inf
70%	1	35	53	156	Inf	Inf	Inf	Inf	Inf	Inf
	5	173	265	781	Inf	Inf	Inf	Inf	Inf	Inf
	10	346	529	1562	Inf	Inf	Inf	Inf	Inf	Inf
	20	692	1058	3125	Inf	Inf	Inf	Inf	Inf	Inf
	30	1038	1587	4687	Inf	Inf	Inf	Inf	Inf	Inf
	40	1384	2116	6250	Inf	Inf	Inf	Inf	Inf	Inf
	50	1730	2646	7812	Inf	Inf	Inf	Inf	Inf	Inf
	60	2076	3175	9375	Inf	Inf	Inf	Inf	Inf	Inf
	75	2595	3968	11719	Inf	Inf	Inf	Inf	Inf	Inf
	100	3460	5291	15625	Inf	Inf	Inf	Inf	Inf	Inf
	125	4325	6614	19531	Inf	Inf	Inf	Inf	Inf	Inf
	200	6920	10582	31250	Inf	Inf	Inf	Inf	Inf	Inf
	360	12457	19048	56250	Inf	Inf	Inf	Inf	Inf	Inf
80%	1	44	80	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	5	222	400	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	10	444	800	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	20	889	1600	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	30	1333	2400	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	40	1778	3200	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	50	2222	4000	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	60	2667	4800	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	75	3333	6000	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	100	4444	8000	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	125	5556	10000	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	200	8889	16000	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	360	16000	28800	Inf	Inf	Inf	Inf	Inf	Inf	Inf
90%	1	59	145	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	5	296	725	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	10	592	1449	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	20	1183	2899	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	30	1775	4348	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	40	2367	5797	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	50	2959	7246	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	60	3550	8696	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	75	4438	10870	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	100	5917	14493	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	125	7396	18116	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	200	11834	28986	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	360	21302	52174	Inf	Inf	Inf	Inf	Inf	Inf	Inf
95%	1	83	476	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	5	413	2381	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	10	826	4762	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	20	1653	9524	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	30	2479	14286	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	40	3306	19048	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	50	4132	23810	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	60	4959	28571	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	75	6198	35714	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	100	8264	47619	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	125	10331	59524	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	200	16529	95238	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	360	29752	171429	Inf	Inf	Inf	Inf	Inf	Inf	Inf
99%	1	123	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	5	617	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	10	1235	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	20	2469	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	30	3704	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	40	4938	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	50	6173	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	60	7407	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	75	9259	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	100	12346	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	125	15432	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	200	24691	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf
	360	44444	Inf	Inf	Inf	Inf	Inf	Inf	Inf	Inf