1. Dataset Limitations

1.1. Population Distributions and Provenance

There are a number of issues with the sample of groups included in the Oswalt et al. (1976) dataset that must be acknowledged. First of all, there are biases towards populations from certain geographic regions that may impact the interpretation of results. For example, by not having a single "arctic/subarctic" grouping, the dataset oversamples each subzone compared to those from temperate, tropical, and desert areas. Furthermore, each of the arctic and subarctic populations derive from a relatively small geographic area worldwide, and therefore there may be common cultural knowledge (and therefore complexity) relating to shared population histories. In this regard, Oswalt et al. (1976: 184) acknowledge some cultural exchange from Western Inuit populations to the Ingalik and Tanaina (Dena'ina). Indeed, this geographic clustering is part of a general bias towards northwestern North America in the dataset, which accounts for more than half of the populations under consideration. At a broader level, however, the sampling patterns reflect the greater study of societies belonging to areas of overall lower carrying capacities, because of a) data collection strategy as outlined above and b) a disproportionate historical displacement of foraging societies who had previously inhabited more productive environments.

Some further issues arise in relation to provenance, in terms of matching toolkits to specific population and/or ecosystems. For instance, Hoffecker and Hoffecker (2018) chose to exclude Tasmanians from the dataset because of Oswalt et al.'s (1976) admission that the toolset described comes from across the (ecologically-variable) island. We have chosen to retain the technological grouping, as we are reusing a metric for complexity that is standardised by the number of artefacts. This should reduce the impact of variation within the cultural repertoire across different parts of the island. However, the dietary and environmental data collated for comparison derive from a single population in the southwest of the island (Binford, 2001), which presents a clear limitation of the dataset. Hoffecker and Hoffecker (2018) also added metrics from the Khoesan groups of the Ju/'hoansi and Hadza, but did not report straightforward technounit averages for these groups, and so we cannot integrate them into Oswalt et al.'s (1976) dataset here.

1.2. Raw Material Availability

While Oswalt et al. (1976) emphasised that resource acquisition was the most important determinant of the toolkit, they also acknowledged the role of other important variables. In particular, raw material availability and its transport may be particularly important in determining how a group considered and manipulated particular substrates. For example, many of the arctic groups in Oswalt et al.'s (1976) dataset occupy environments with limited tree availability for wood collection, which has likely played an important role in how the material is treated upon encounter. The lack of information on material sources and abundance is therefore another important weakness of the dataset.

2. Associations between non-technological variables

Figure S1 shows the relative proportions that gathering, hunting, and fishing contribute to the diets of each population. There is a large amount of variation, with hunting the only ever-present dietary strategy, although it can still be quite limited in its pursuit amongst some arctic and subarctic populations. The proportion of gathering in the dataset is not associated with the proportion of hunting (r = -0.023, p = 0.924) but is negatively associated with the proportion of fishing (r = -0.874, p = 4.693e-07). Hunting is also negatively associated with fishing (r = -0.465, p = 0.039). Gathering is completely absent among the Angmagsalik, Caribou Inuit, Copper Inuit, Iglulik Inuit, and Tareumiut, but contributes >50% of the diet among the Andamanese, Chenchu, and Naron. Fishing has not been recorded among the Aranda and Naron, but represents ≥50% of the diet among the Angmagsalik, Copper Inuit, Iglulik Inuit, Ingalik, Ingura, Klamath, Nabesna, Tareumiut, Tasmanians, Tlingit, and Twana. This predominance of fishing in 11/20 societies highlights a bias towards fisher-foragers in the present dataset.

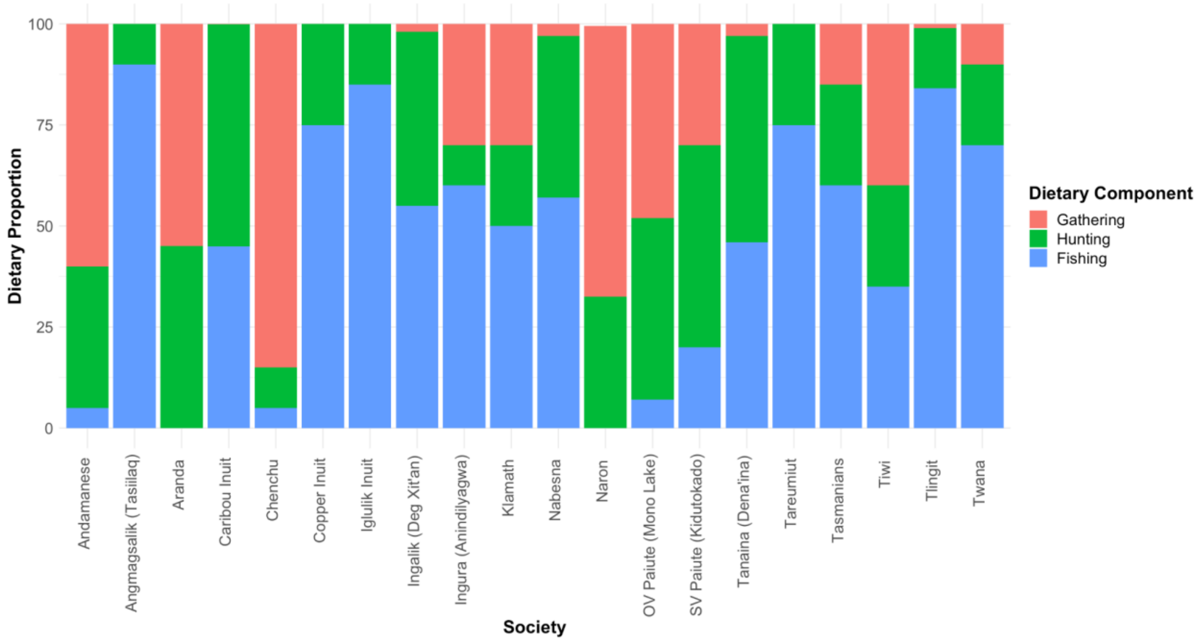


Figure S1. Relative contributions of gathering, hunting, and fishing to the diets of each society in the dataset. Data derived from Binford (2001) through d-Place.

With regards to demography, there is notable variation in DFI and particularly population density; among these populations, we find a negative relationship between each of these variables when the latter is placed on a logarithmic scale (r = -0.850, p = 2.061e-06; Figure S2). This suggests that these populations pursue a strategy of fewer moves over larger distances when population density is lower, whereas higher density populations move over shorter distances more often. The log of maximum aggregated group size is not associated with DFI in the present dataset (r = 0.175, p = 0.460), nor with population density (r = -0.191, p = 0.419).

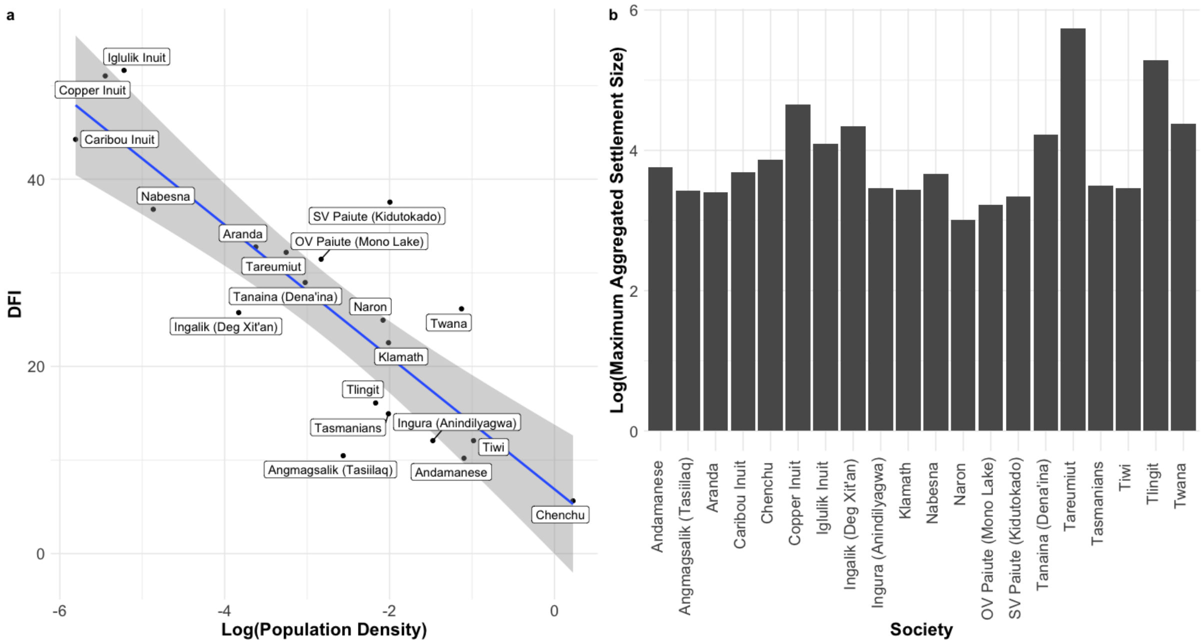


Figure S2. Summary of key demographic variables for each of the societies in the dataset. a = the relationship between the movement distance/frequency index (DFI), with higher scores equating to fewer moves but longer distances and log population density. b = log maximum aggregated settlement size.

DFI is inversely associated with dietary gathering (r = -0.453, p = 0.045), while the reverse is true of log population density (r = 0.622, p = 0.003), suggesting the DFI-density relationship is being driven by the increased exploitation of plant resources: where these are more common, you get more dense populations who move shorter distances more often. Increased gathering also reduces the size of maximum aggregations (r = -0.528, p = 0.017), suggesting groups stay relatively small, but dense throughout the year. Combined, this strategy may represent the optimal conditions for hunter-gatherers in behavioural ecological models, as their dietary returns are met with the least energetic investment (Grove et al., 2023). Hunting is associated with log-transformed population density (r = -0.406, p = 0.075) and DFI (r = 0.450, p = 0.047) in opposite directions, suggesting populations carrying out this strategy support a lower density of people at individual bases, but over a longer period of time, before longer-distance movement to new resource patches. At the same time, hunting has no impact on the size of maximum yearly aggregations (r = -0.207, p = 0.381). Fishing is not clearly associated with either log population density (r = -0.353, p = 0.127), or DFI (r = 0.183, p = 0.441), but does create larger maximal groupings (r = 0.568, p = 0.009).

As expected from the discussion of population distributions above, we see a strong bias towards areas with low monthly rainfall and monthly rainfall variance (seasonality), as well as areas with low NPP and NPP seasonality, and low temperature seasonality (Figure S3). These distributions show clear positive skews, which are log-transformed in all subsequent correlations. There is a relatively more uniform distribution of populations from different absolutely monthly temperature regimes. As shown in Table S1, NPP is moderately associated with the temperature and rainfall variables. Each of the rainfall and temperature variables are strongly associated with one another, indicating: higher rainfall is associated with greater seasonality of that rainfall, greater mean temperatures, and reduced temperature seasonality. This is expected for lower latitude environments. Lower rainfall is associated with reduced rainfall seasonality, lower mean temperatures, and increased temperature seasonality, as expected at higher latitudes. While the overall differences in climatic conditions between the two regions are expected, it is important to underline that populations are likely to respond to seasonality differently in each: temperature seasonality should be the greatest pressure on behaviour in higher latitudes, and rainfall seasonality in lower latitudes. This is underlined by the strong negative association between the log-transformations of rainfall seasonality and temperature seasonality ($r = -0.848$, $p = 2.401e-06$).

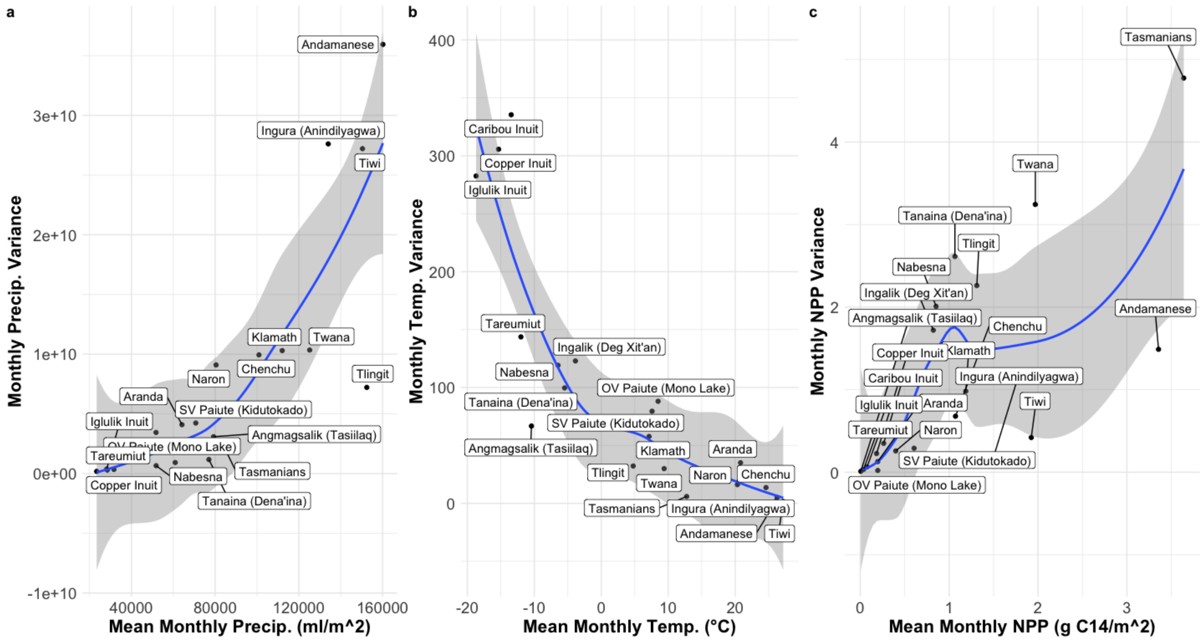


Figure S3. Summary of environmental variables in each population, relating to precipitation (a), temperature (b), NPP (c), and their seasonality (as measured by their variances). There is a positive skew amongst monthly rainfall, and NPP, as well as their seasonalities and temperature seasonality, reflecting a bias towards populations with lower carrying capacities.

Variable	Log(Mean Monthly Precip.)	Log(Monthly Precip. Variance)	Mean Monthly Temp.	Log(Monthly Temp. Variance	Log(Mean Monthly NPP)	Log(Monthly NPP Variance)
Dietary Variables						
%Gathering	0.434†	**0.663****	**0.823*****	**-0.593****	0.297	-0.042
%Hunting	-0.298	-0.296	-0.139	0.317	0.101	0.126
%Fishing	-0.239	-0.443†	**-0.661*****	0.371	-0.311	-0.024
Demographic Variables						
DFI	**-0.843*****	**-0.774*****	**-0.693*****	**0.807*****	-0.396†	-0.248
Log(Pop. Density)	**0.842*****	**0.863*****	**0.801*****	**-0.799*****	**0.491***	0.248
Log(Yearly Distance)	**-0.605****	**-0.486***	-0.345	**0.462***	-0.108	-0.148
Yearly Moves	-0.387†	-0.242	-0.085	0.158	-0.022	-0.145
Log(Maximum Aggregated Settlement)	-0.260	-0.423†	**-0.461***	0.332	-0.075	0.150
Climatic Variables						
Log(Mean Monthly Precip.)	—	**0.924*****	**0.776*****	**-0.819*****	**0.625****	**0.456***
Log(Monthly Precip. Variance)	**0.924*****	—	**0.892*****	**-0.848*****	**0.510***	0.198
Mean Monthly Temp.	**0.776*****	**0.892*****	—	**-0.891*****	**0.611****	0.250
Log(Monthly Temp. Variance)	**-0.819*****	**-0.848*****	**-0.891*****	—	**-0.596****	-0.304
Log(Mean Monthly NPP)	**0.625****	**0.510***	**0.611****	**-0.596****	—	**0.860*****
Log(Monthly NPP Variance)	**0.456***	0.198	0.250	-0.304	**0.860*****	—

Table S1. Relationships between different climatic characteristics of each population and the dietary, demographic, and other climatic variables. $^{\dagger}p<0.1$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$.

With regards to diet, Table S1 also highlights that increased rainfall seasonality is associated with increased plant consumption, as is increased temperature and decreased temperature seasonality. This again suggests greater plant availability in lower latitudes, which accounts for the relationships between the rainfall and temperature variables and DFI, population density, distance moved in a year, and maximum size of aggregated settlements. The number of yearly moves is only associated with increased temperature seasonality.

3. Additional Technological Information

Figures S4 and S5 depict the technological diversity seen across the different groups present in the Oswalt et al. (1976) dataset. Figure S4 shows the relative proportion of instruments, weapons, tended facilities, and untended facilities in each society, while Figure S5 depicts the average technounit complexity for each of these categories.

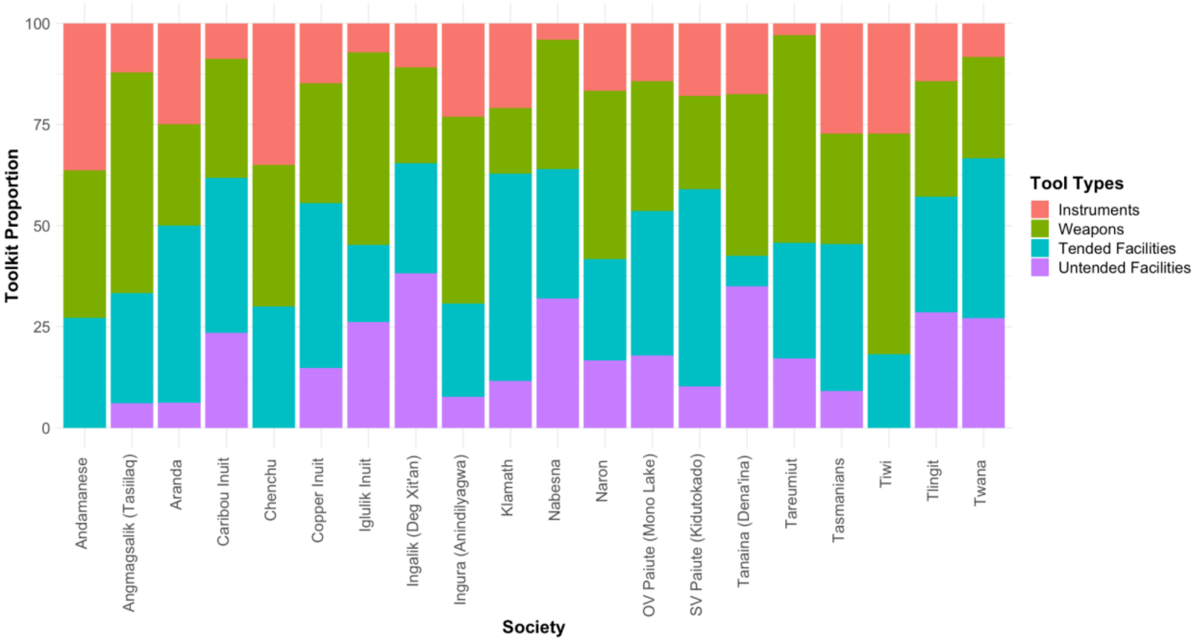


Figure S4. Toolkit proportions according to the four tool subtype of Oswalt et al. (1976).

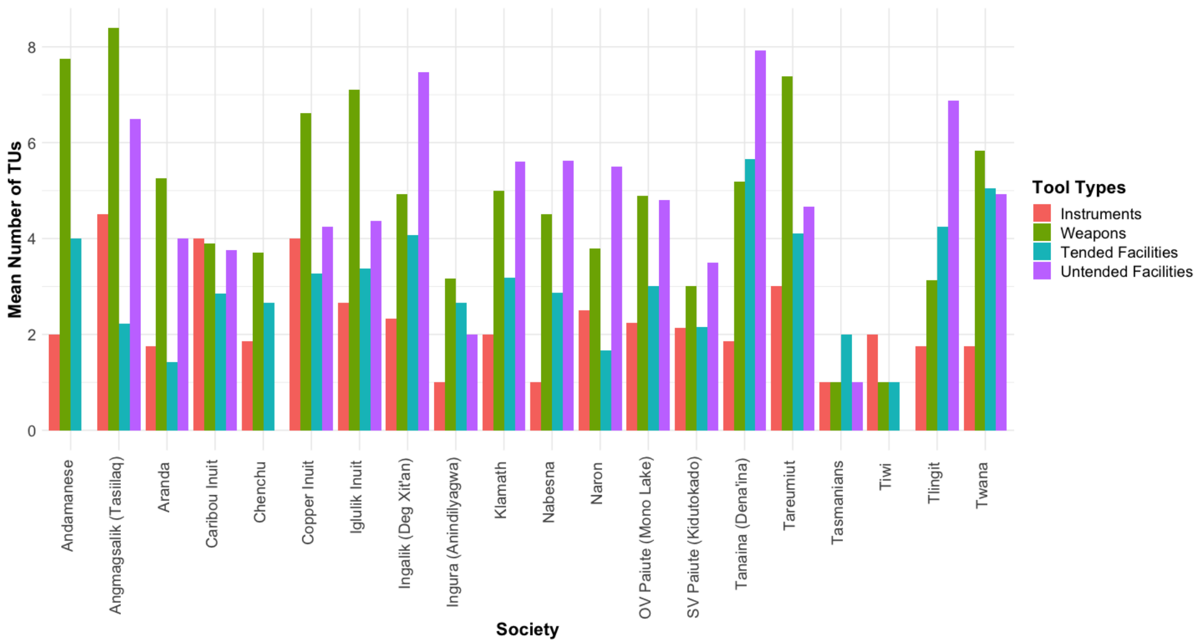


Figure S5. Average number of technounits for each tool subtype.

4. Bivariate Technological Relationships

Tables S3-S6 display the complete bivariate relationships that are partially displayed in Tables 3-6. These include relationships between technological variables (Table S3), between dietary and technological variables (Table S4), between demographic and technological variables (Table S5), and between climatic and technological variables (Table S6).

Variable	%Instr.	Mean Instr. TUs	%Weap.	Mean Weap. TUs	%TF	Mean TF TUs	%UF	Mean UF TUs	Total n
%Instr.	—	-0.358	-0.061	-0.331	-0.005	-0.331	**-0.737*** **	-0.402	**-0.629** **
Mean Instr. TUs	-0.358	—	0.264	**0.538***	0.060	-0.022	-0.017	0.208	0.284
%Weap.	-0.061	0.264	—	0.120	**-0.730*** **	-0.158	-0.239	0.048	-0.300
Mean Weap. TUs	-0.331	**0.538***	0.120	—	-0.041	0.437†	0.115	0.431†	0.375
%TF	-0.005	0.060	**-0.730*** **	-0.041	—	-0.244	-0.206	-0.382	0.135
Mean TF TUs	-0.331	-0.022	-0.158	0.437†	-0.244	—	**0.633** **	**0.548***	**0.560** **
%UF	**-0.737*** **	-0.017	-0.239	0.115	-0.206	**0.633** **	—	**0.627** **	**0.665** **
Mean UF TUs	-0.402	0.208	0.048	0.431†	-0.382	**0.548***	**0.627** **	—	**0.547***
Total n	**-0.629** **	0.284	-0.300	0.375	0.135	**0.560** **	**0.665** **	**0.547***	—
Mean Total TUs	**-0.593** **	**0.467***	0.187	**0.841*** **	-0.278	**0.710*** **	**0.547***	**0.738*** **	**0.625** **

Table S3. Relationships between different technological variables in the dataset. †p<0.1, *p<0.05, **p<0.01, ***p<0.001.

Variable	%Gathering	%Hunting	%Fishing
%Instruments	**0.744(<0.001)*** **	-0.141(0.553)	**-0.589(0.006)** **
Mean Instrument TUs	-0.311(0.182)	0.020(0.933)	0.265(0.259)
%Weapons	-0.032(0.893)	-0.366(0.113)	0.206(0.385)
Mean Weapons TUs	-0.229(0.332)	-0.095(0.689)	0.249(0.290)
%Tended Facilities	0.091(0.702)	0.138(0.561)	-0.147(0.535)
Mean TF TUs	**-0.446(0.049)* **	0.049(0.837)	0.371(0.107)
%Untended Facilities	**-0.647(0.002)** **	0.339(0.150)	0.409(0.073)†
Mean UF TUs	-0.240(0.354)	0.127(0.628)	0.115(0.661)
Total n	**-0.579(0.007)** **	0.152(0.522)	0.439(0.053)†
Mean Total TUs	**-0.525(0.017)* **	-0.033(0.889)	**0.481(0.032)* **

Table S4. Relationships between technological variables and dietary components. †p<0.1, *p<0.05, **p<0.01, ***p<0.001.

Variable	Log(Pop. Density)	Log(Yearly Distance)	Yearly Camp Moves	DFI	Log(Maximum Aggregated Settlement)
%Instruments	**0.661****	-0.311	0.029	**-0.635****	-0.407†
Mean Instrument TUs	**-0.453***	0.089	0.059	0.354	0.157
%Weapons	0.083	-0.316	-0.185	-0.205	0.067
Mean Weapons TUs	-0.309	0.042	-0.016	0.265	0.314
%Tended Facilities	-0.068	0.393†	0.318	0.232	-0.168
Mean TF TUs	-0.094	-0.122	-0.319	0.133	**0.654****
%Untended Facilities	**-0.546***	0.194	-0.134	**0.493***	0.413†
Mean UF TUs	-0.073	-0.383	-0.463†	-0.059	0.295
Total n	-0.334	0.105	-0.238	0.423†	0.377
Mean Total TUs	-0.368	-0.112	-0.292	0.268	**0.548***

Table S5. Relationships between technological variables and demographic information. $^{\dagger}p<0.1$, *p<0.05, **p<0.01, ***p<0.001.

Variable	Environmental Baseline			Environmental Seasonality			Environmental Predictability		
	Log(Precip.)	**Temp.**	**Log(NPP)**	**Log(Precip.)**	**Log(Temp.)**	**Log(NPP)**	**Precip.**	**Temp.**	**NPP**
%Instr.	**0.613****	**0.799*****	**0.512***	**0.681*****	**-0.769*****	0.246	-0.353	**0.800*****	**-0.741*****
Mean Instr. TUs	**-0.553***	**-0.595****	**-0.749*****	**-0.475***	**0.531***	**-0.585****	-0.047	**-0.484***	**0.704*****
%Weap.	-0.046	-0.038	-0.427†	0.029	-0.212	**-0.512***	-0.033	0.211	0.161
Mean Weap. TUs	-0.374	**-0.486***	**-0.613****	-0.314	**0.451***	-0.433†	-0.024	-0.434†	**0.534***
%TF	-0.116	0.018	0.032	-0.027	0.206	0.014	-0.245	-0.139	0.050
Mean TF TUs	-0.040	-0.393†	0.139	-0.228	0.341	0.357	**0.500***	-0.406†	0.153
%UF	-0.343	**-0.619****	-0.035	**-0.547***	**0.629****	0.274	**0.533***	**-0.713*****	0.395†
Mean UF TUs	0.097	-0.347	-0.168	-0.079	0.395	0.090	0.094	**-0.574***	0.216
Total n	-0.323	**-0.651****	-0.262	-0.441†	**0.703*****	0.009	0.297	**-0.734*****	**0.529***
Mean Total TUs	-0.353	**-0.678****	**-0.512***	**-0.450***	**0.583****	-0.205	0.276	**-0.633****	**0.596****

Table S6. Relationships between technological variables and climatic characteristics. †p<0.1, *p<0.05, **p<0.01, ***p<0.001.

5. Path analysis

Figure S6 shows that there are many strong relationships between the demographic, dietary, ecological and technological variables. To explore the potential hierarchical structure of these relationships between variables, we applied path analysis, a form of structural equation modelling (SEM). Path analysis uses multiple regression statistical analyses to evaluate causal models by examining the relationships between a dependent variable and many independent variables. Specifically, we use path diagrams to test the relationship between the demographic and/or ecological variables highlighted as having significant independent effects on technology within a pre-determined structure: technology is the independent variable and climate, demography and dietary composition are the dependent variables, with demography and diet also a function of climate (Figure S7). We use this highly complex modelling method as a way of dealing with the hierarchical and interdependent nature of the variables we employ, with the caveat that such methods are generally more robust when applied to much larger samples; our model fit indices indeed suggest that the SEM results require testing with more data to confirm these hypothesised relationships (Table S7).

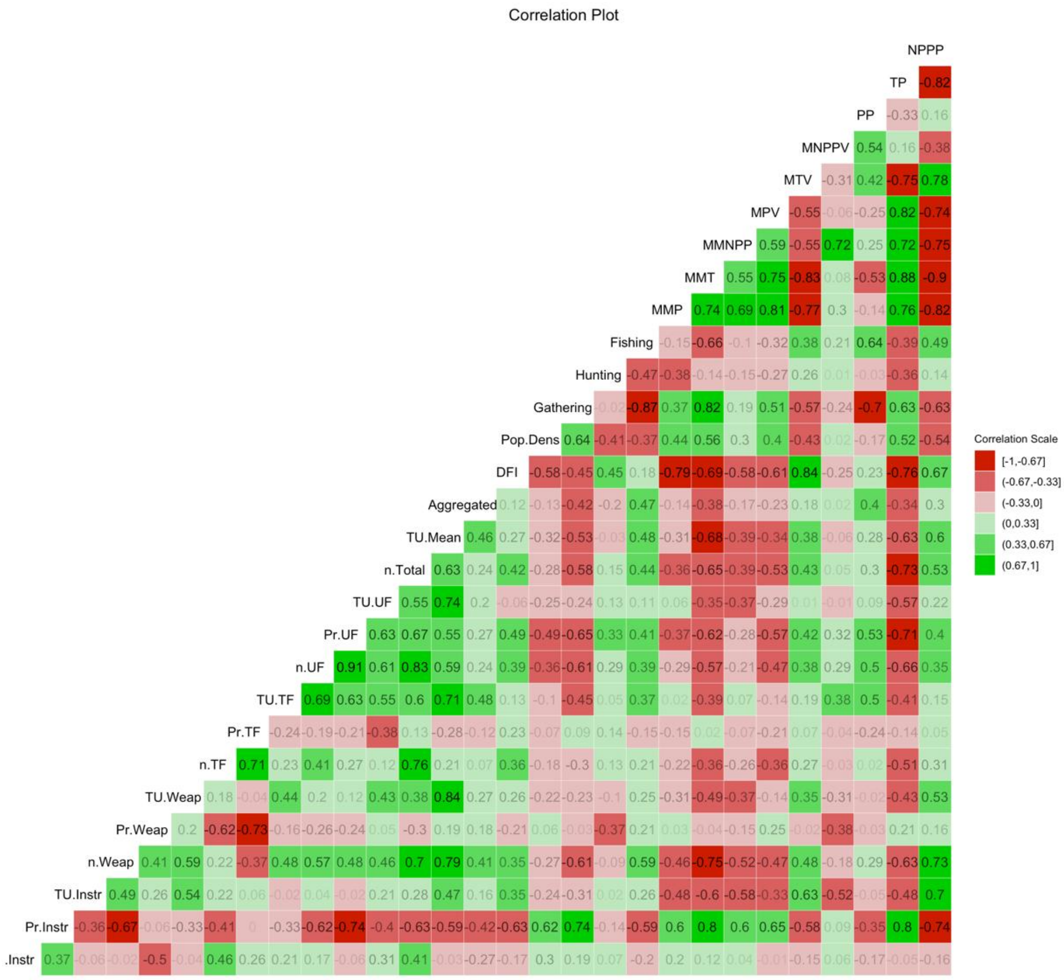


Figure S6. Correlation plot of all variables considered in this analysis. NB. These have not been scaled.

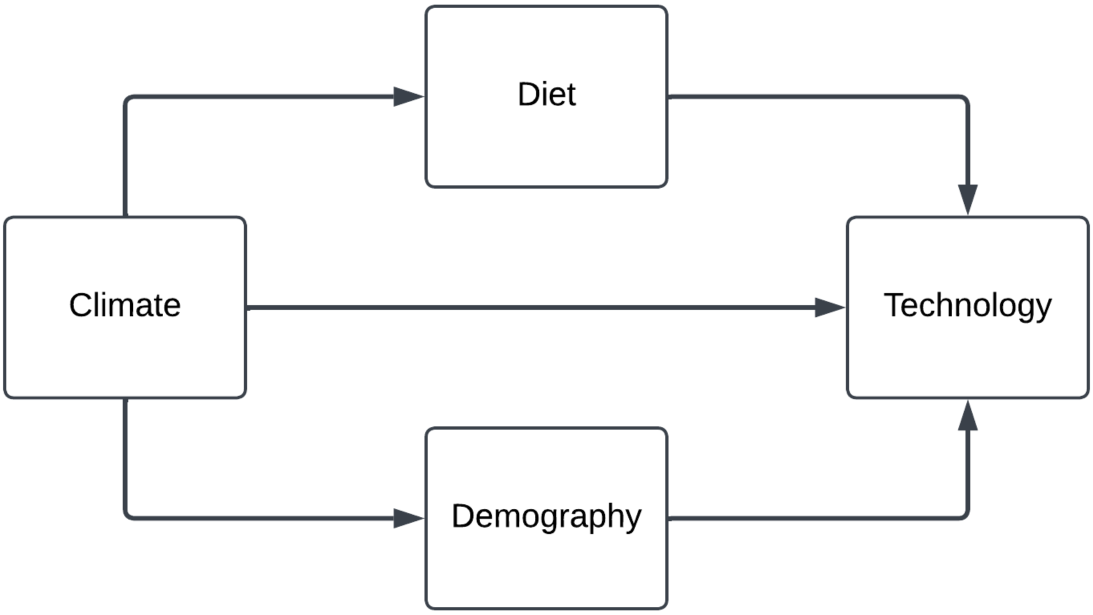


Figure S7. Structure of variable input for the Path Analysis, based on the logic we present in Section 2.

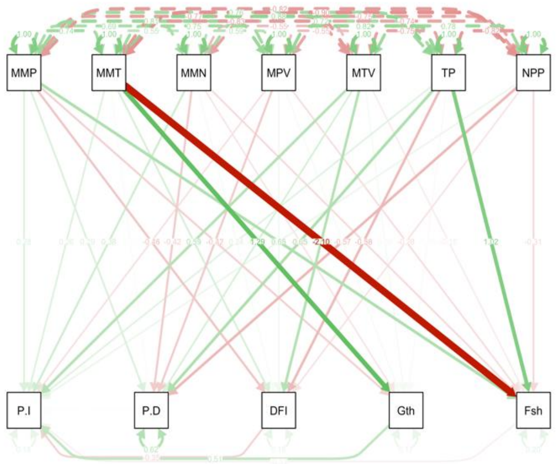
	N param	P value (Chi square)	CFI	TLI	RMSEA	SRMR	AIC	BIC	aBIC
%Instr	44	< 0.001	0.77	-0.671	0.505	0.042	220.706	264.518	128.877
TU Instr	19	0.012	1.00	1.00	0.00	0.00	116.814	135.733	77.161
TU Weap	5	0.126	1.00	1.00	0.00	0.00	58.544	63.522	48.109
TU TF	8	0.097	0.845	0.069	0.297	0.109	168.598	176.564	151.902
%UF	27	< 0.001	0.839	-0.398	0.504	0.046	174.556	201.441	118.207
n.Total	11	<0.001	1.00	1.00	0.00	0.00	82.409	93.362	59.452
Mean TU	31	<0.001	0.824	-0.756	0.513	0.035	183.757	214.625	119.1060

Table S7. Model fit indices. Chi-square p-value: non-significant results = good model fit, comparative fit index > 0.90 = good fit, Tucker-Lewis Index > 0.90 = good fit, root mean square error of approximation < 0.08 = good fit, standardised root mean residual < 0.08 = good fit. Red = bad fit, green = good fit.

5.1. Instruments

Based on our simple correlation statistics, percentage of instruments has independent relationships with gathering (+), fishing (-), population density (+), DFI (-), precipitation (+), temperature (+), NPP, (+) precipitation seasonality (+), temperature seasonality (-), temperature predictability (+) and NPP predictability (-) (Figure S6). Using SEM, we find that gathering (0.51, p = 0.025) and temperature seasonality (0.58, p = 0.032) have direct significant positive impacts on the percentage of instruments in the toolkit (Figure S8). For temperature seasonality, this is the inverse relationship identified in the simple correlations, highlighting the potential for unreliability when using this highly complex method. Temperature is a significant positive indicator of gathering (1.289, p = 0.005) and negative indicator of fishing (-2.099, p < 0.001), whereas temperature predictability is a significant positive indicator of fishing (1.024, p = 0.004). Temperature seasonality is a significant positive indicator of DFI (0.601, p = 0.01).

Based on our simple correlations, mean techno-units of instruments has independent relationships with population density (-), precipitation (-), temperature (-), NPP (-), precipitation seasonality (-), temperature seasonality (+), NPP seasonality (-), temperature predictability (-) and NPP predictability (+) (Figure S6). The SEM model suggests that none of these dependent variables can be considered to have significant direct relationships on mean techno-units of instruments, when taking the hierarchical structure of their relationships. Nonetheless, precipitation (0.55, p = 0.15) and NPP predictability (0.55, p = 0.365) have the strongest positive association with the complexity of instruments, with NPP seasonality having a strong negative association (-0.71, p = 0.237) (Figure S8).



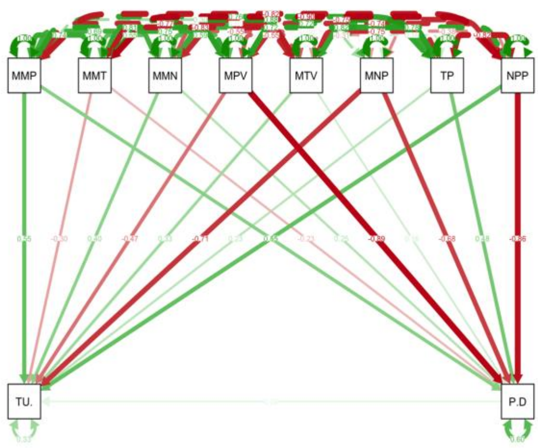


Figure S8. Left = Percentage of instruments, right = TUs of instruments. NB. All variables have been scaled.

5.2. Weapons and tended facilities

Percentage of weapons within the toolkit is only significantly associated with NPP in our simple correlations therefore we do not construct an SEM for this technological variable. Similarly, percentage of tended facilities show no significant relationships with any of the explanatory variables. For the complexity of weapons (mean TUs), only climatic variables are found to have significant correlations, specifically temperature (-), NPP (-), temperature seasonality (+) and NPP predictability (+) (Figure S6). Our SEM suggests that NPP predictability has the strongest (positive) impact on the complexity of weapons (0.589, p = 0.317) with the other variables having minimal association (Figure S9).

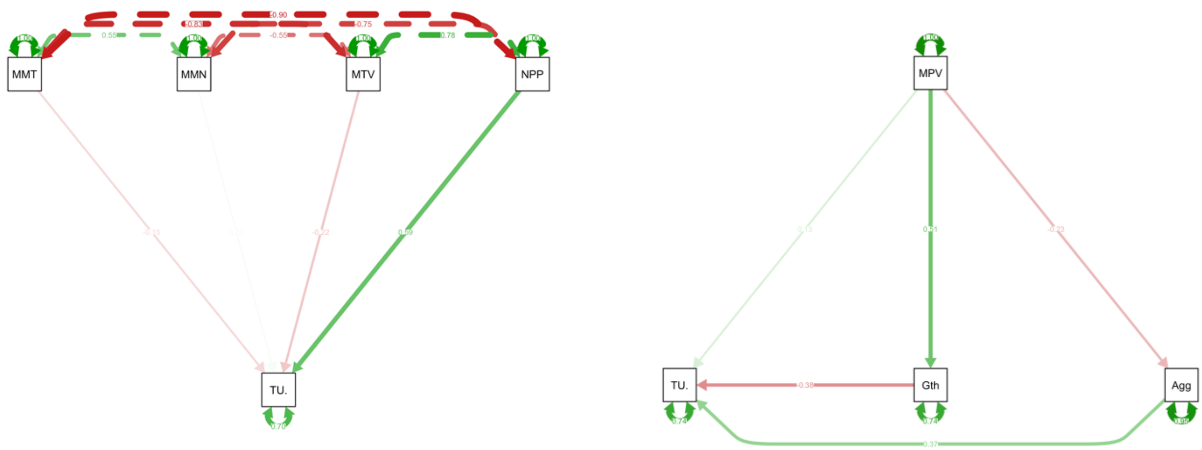


Figure S9. Left = Mean technounits of weapons, right = Mean technounits of tended facilities. NB. All variables have been scaled.

Mean technounits of tended facilities show significant independent relationships with gathering (-), aggregated settlement size (+) and precipitation seasonality (+) (Figure S6). Figure S9 shows that precipitation seasonality has a significant positive impact on gathering (0.509, p = 0.008), which in turn has a negative relationship with the complexity of tended facilities (-0.362, p = 0.092). Alternatively, precipitation seasonality has a negative relationship with the size of seasonal aggregations (-0.231, p = 0.289) which in turn has a positive relationship with the complexity of tended facilities (0.355, p = 0.062). Precipitation seasonality has a weak positive direct effect on the technounits of tended facilities (0.128, p = 0.560).

5.3. Untended facilities

The complexity of untended facilities was not found to have any significant associations, and therefore no SEM was constructed for this variable. For the percentage of untended facilities in the toolkit, gathering (-), population density (-), DFI (+), temperature (-), precipitation seasonality (-), temperature seasonality (+), precipitation predictability (+) and temperature predictability (-) were found to have significant associations (Figure S6). Our SEM (Figure S10) found that only precipitation (0.486, p = 0.004) and temperature predictability (-1.109, p = 0.001) have direct significant relationships in opposing directions. Temperature (1.143, p < 0.001) and precipitation predictability (-0.312, p = 0.008) have significant impact on gathering, which in turn has a negative relationship with the percentage of untended facilities (-0.141, p = 0.603). DFI has a significant positive association with temperature seasonality (0.844, p < 0.001), which in turn has a weak but positive relationship with the percentage of untended facilities (0.020, p = 0.936).

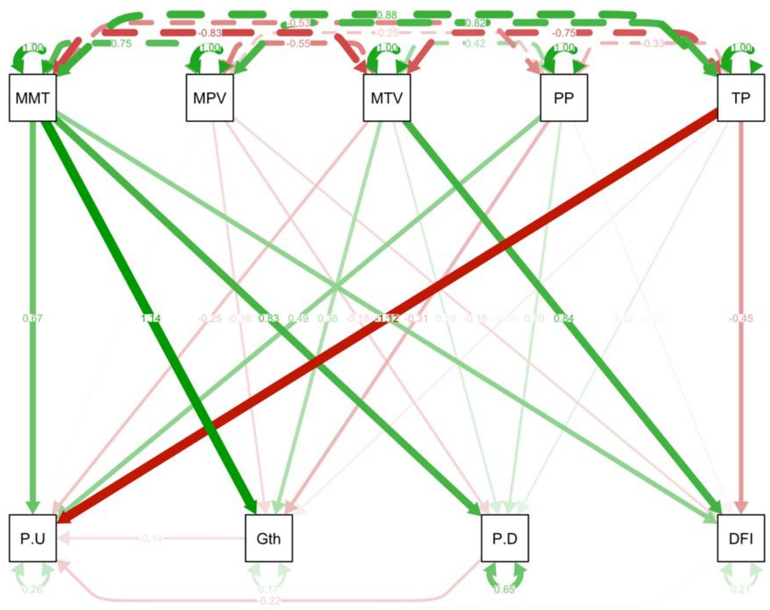


Figure S10. Percentage of untended facilities. NB. All variables have been scaled.

5.4. Overall toolkit

Total number of tools was found to have a significant relationship with gathering (-), temperature (-) and its seasonality (+) and predictability (-), as well as NPP predictability (+) (Figure S6). Using SEM (Figure S11), we found that only temperature predictability has a significant direct (negative) impact on the number of tools within a toolkit (-0.860, p = 0.007). Gathering is significantly associated with higher temperatures (1.807, p < 0.001) and more predictable NPP (0.503, p = 0.031), which in turn has a negative relationship with the total number of tools (-0.191, p = 0.537). Mean complexity (TUs) was found to have significant correlations with gathering (-), fishing (+), size of seasonal aggregations (+), temperature (-), NPP (-), precipitation (-) and temperature (+) seasonality, and temperature (-) and NPP (+) predictability (Figure S6). Our SEM (Figure S11) suggests that gathering has a significant direct positive impact on average complexity (0.789, p < 0.001), as well as precipitation seasonality (0.87, p < 0.001). Conversely, temperature (-1.591, p = 0.026), its seasonality (-0.847, p < 0.001) and predictability (-0.957, p = 0.010) have significant direct negative impacts on overall complexity. However, temperature has a higher positive association with gathering (1.557, p < 0.001) as well as a strong negative relationship with fishing (-2.576, p < 0.001), which although counter-intuitive suggests that raw temperatures have a greater influence on the adoption of specific food procurement strategies, whilst the variability of temperature in time has a stronger impact on toolkit complexity.

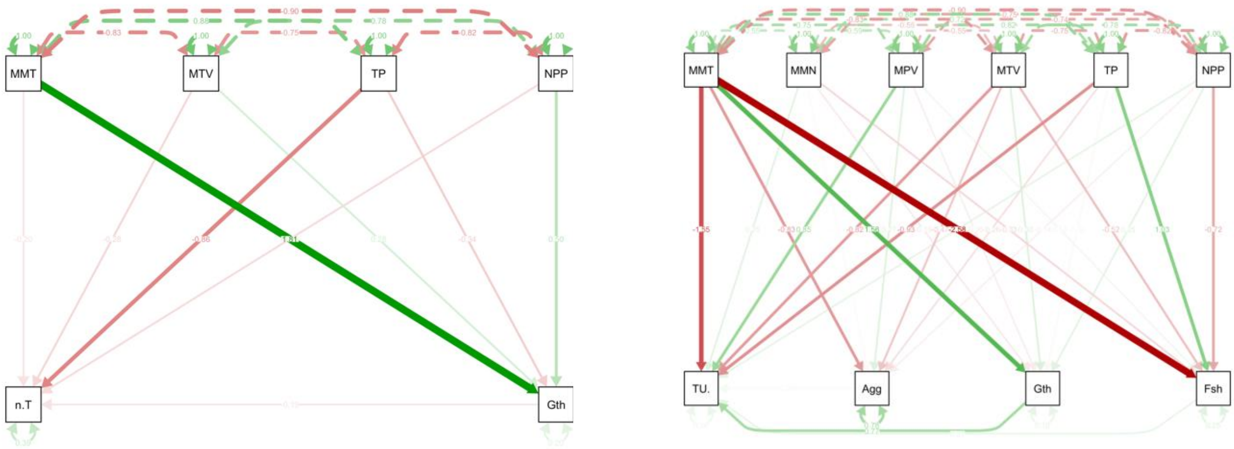


Figure S11. Left = Total number of tools, right = Average TUs. NB. All variables have been scaled.